UNIVERSITY OF LJUBLJANA
FACULTY OF ECONOMICS

MASTER'S THESIS

PREDICTING BORROWER'S DEFAULT BY FINANCIAL AND NON-FINANCIAL INDICATORS IN DISCRIMINANT ANALYSIS FUNCTION

Ljubljana, May 2015 KATJA ŽGUR

AUTHORSHIP STATEMENT

The undersigned Katja Žgur, a student at the University of Ljubljana, Faculty of Economics, (hereafter: FELU), declare that I am the author of the master's thesis entitled Predicting Borrower's Default by Financial and Non-financial Indicators in Discriminant Function Analysis, written under supervision of prof. dr. Marko Košak.

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INTRODUCTION

Internal ratings in commercial banks are defined by Crouhy, Galai and Mark (2001) as the process used to classify bank borrowers into categories of different credit riskiness. A certain rating class represents the probability of default by a borrower or group in repaying its obligation in the normal course of business. To derive internal grade to the borrower, rating systems in banks mostly consist of both, financial (quantitative) and non-financial (qualitative) evaluation. Non-financial indicators, according to Bessis (2002), describe qualitative assessment of the counterparty's credit standing, while quantitative variables are mainly financial variables that can be derived from the company's financial statements.

According to Crouhy et al. (2001), financial indicators can be divided into three main assessment areas: (1) earnings and cash flows, (2) asset values, liquidity and leverage, and (3) flexibility and debt capacity. Bessis (2002) on the other hand, divides financial variables into the following categories: operating profitability, financial profitability, financial structure, cash flow, operating efficiency, operating leverage, liquidity, market value and volatility of earnings and sales.

With regard to Bessis (2002), most common, non-financial indicators that are included into the rating models are industry, competition, market share and size, diversification of products and services, country risk, growth potential, technology, quality of products and services, management quality and barriers to entry. Crouhy et al. (2001) added day-to-day account operations as well, environmental assessment and contingent liabilities, quality of the information provided by the company, third-party support and presence of collateral. Volk (2012) found that one of the most important non-financial indicators are also a company's age and a variable, which measures a number of days per year a company has blocked a bank account.

According to Grunert, Noreden and Weber (2005), the eligibility of financial indicators as inputs for internal credit ratings is already widely accepted, while the role of non-financial indicators remains ambiguous. Non-financial indicators are also usually less available to gather. This is why the academic research on inclusion of different non-financial indicators in rating models is so interesting. Could non-financial indicators give us an additional insight to the state and the future prospect of the company and could inclusion of non-financial indicators contribute to the accuracy of default predictions? This is the main **research question** of my thesis and the question I will strive to answer. I set the following **hypothesis**: A model that consists of a combination of financial and non-financial indicators, leads to a better prediction of company's default, than a model consisting of only accounting or financial indicators. So, the **purpose** of the thesis is to analyze non-financial indicators and their contribution to internal ratings, while different indicators that are inputs for ratings are the **subject** of my research. My main **objective** is to find out if the inclusion of non-financial indicators leads to a higher percent of cases correctly classified, when using discriminant analysis function.

For my research, **motivation** is derived from the fact that most research on corporate prediction modelling is based on accounting or financial ratios, while non-financial indicators are rarely included in the modelling. Grunert et al. (2005) mentioned that there is a lack of quantitative research on this issue. Nevertheless, few authors have already studied the subject. Grunert et al. (2005) analyze data from four major German banks and found evidence that the combined use of financial and non-financial indicators leads to a more accurate prediction of future default events, than the single use of each of these indicators. Ciampi (forthcoming 2015) included corporate governance variables and found that they significantly improve the small enterprises default prediction of accuracy rates.

To verify the hypothesis, I'm going to use a discriminant function analysis that shows a percentage of correctly classified units in original groups. Firstly, I'm going to select a sample of corporate borrowers. Further on, I'm going to form two groups of those corporates in Slovenia; companies that defaulted and are now in bankruptcy and companies that are active in the market. I'm going to divide these two groups with a rule set by the discriminant function, where variables will be indicators that could be included in internal ratings in banks. The first function will consist of financial indicators only (gathered from accounting data) and the second one will include non-financial indicators as well. I expect that the percent of cases correctly classified will be higher in the second function than in the first one. Furthermore, I expect that the variability, explained by additional non-financial indicators included, will be higher as in the case of function with only financial indicators.

When deciding which financial and non-financial indicators should be included in my analysis, I will also rely on the findings, gathered from the interview with the Head of Risk Management Department in one of the Slovenian banks. Since ratings have an important role in the loan approval decisions, the indicators that serve as inputs for rating models are very important as well.

In my master thesis, I will firstly describe the risk that banks try to assess with internal ratings, credit risk, and its components; probability of default (hereinafter: PD), loss given default (hereinafter: LGD) and exposure at default (hereinafter: EAD). Secondly, I will move to the core subject of the thesis – rating systems and describe external and internal ratings. I will concentrate on internal ratings and write about internal rating process in banks and regulation on internal ratings. Furthermore, I will describe indicators that influence on internal ratings and divide them into financial and non-financial. To answer my research question, I will present other authors' research in the field of non-financial indicators in internal ratings. Later on, I will write about the role of ratings in loan approval decisions and then present models that are used when designing internal ratings. I will separately describe models that could be used for predicting company's default; linear probability model, logit model, probit model and discriminant function analysis. The empirical part of the thesis will be followed, where I will first present methodology; research design, sample structure and criteria, and indicators used in the analysis. Then I will show results of the analysis and findings. In addition, I will present possibilities for the further research.

1 CREDIT RISK

Credit risk is defined as risk that borrowers or different counterparties in bond or derivatives markets could default (Hull, 2012). According to Van Greuning and Brajovic Bratanovic (1999), bank failure is in majority of cases caused because of credit risk. Borrowers may delay on payments or at the end even not repay a loan, which can cause bank's liquidity problems. Van Greuning and Brajovic Bratanovic (1999) define three main types of credit risk: country risk, corporate risk and personal risk. In my master thesis, I will focus on corporate credit risk.

Glantz (2003) emphasizes that there is always the possibility for borrower not to repay the bank debt, however PD for the typical company is around 2%. According to written, chance of default seems to be quite small, but the variation of probabilities of default across companies in the market is quite high. Average lowest rated company, has according to Glantz (2003), 4% PD, while PD for average best–rated company is 0.02%. This resulted in 200 times difference. Although PDs are not presented in high numbers, credit risk can increase quickly.

There are many definitions of default. Bessis (2002, p. 437) argues that those definitions are: "missing a payment obligation for a few days, missing a payment obligation for more than 90 days, filing for bankruptcy, restructuring imposed by lenders and breaking a covenant triggering a cross-default for all lenders to the same entity". According to Crouhy et al. (2001), default events are bankruptcy and restructuring, because in this case, the obligations not paid are major. Bankruptcy is usually the final point in the company's existence, because at that time, it is clear that company cannot pay their obligations.

In conclusion, He, Gong and Xie (2008) argue that several defaults from bank corporate borrowers can have major impact on bank profitability. For this reason, credit risk management is very important in commercial banks. The credit risk management components that are considered in banks are PD, LGD and EAD. Glantz (2003) also adds the fourth - maturity. In the following chapter, I will briefly describe risk components one by one, starting with the PD.

1.1 Probability of default (PD)

With regard to Glantz (2003, p. 500): "PD is the probability that the counterparty or borrower will fail to service its obligation". PD for a corporate borrower in bank is usually estimated for each company that has a loan.

Before the default event, there is difficult with certainty distinguish between companies that are going to default and the ones that not. So the PD assessments are only predictions based on facts about the borrower and estimates of the default's likelihood.

To predict default of the company or calculate PD, banks use different models and approaches. Blochlinger (2012) stated that the models that can estimate good default predictions about the borrowers are for bank very important. He even argues that those models are crucial for bank's

survival in the market. Furthermore, PD is for risk management key input factor and component of the review process made by supervisors. Tasche (2006) stated that PDs are also used for pricing calculations, loan approval decisions and allocations of regulatory and internal capital. Granting capital is not determined only on PD, but also on LGD and EAD parameters, which I will describe next.

1.2 Loss given default (LGD)

Glantz (2003, p. 500) defines LGD as: "The extent of the loss incurred in the event the borrower or counterparty defaults". He argues that LGD depends on the seniority of the facility and the collateral's quality. With regard to Crouhy et al. (2001), the presence of collateral have huge impact on the calculation of LGD. It shows the quality of the amount that will be used for reducing bank's loss.

Bessis (2002, p. 439) defines the LGD in the equation 1 below. LGD in equation 1 is calculated as the exposure multiplied with 1 minus percent of recovery rate. He argues that recoveries require a lot of time, expenses and legal procedures and thus cannot be certain.

$$LGD = exposure \times (1 - recovery\ rate\ \%) \qquad (1)$$

Basel Committee on Banking Supervision (2000) made a survey about the internal rating systems and also asked about the LGD calculations used in banks. The survey include around thirty banks in the G-10 countries, with well-developed internal rating systems and relevant national supervisors. Banks were asked different questions, also about the indicators that from their experience are noted as important to LGD predictions. Among others, Basel Committee on Banking Supervision (2000) found that four most important pointed out were:

- borrower attributes, that include borrower's internal rating grade, country of origin or country within majority of business is made, size, industry and other indicators, which could affect defaulted borrower's unsecured value remaining,
- facility characteristics, such as existence of credit risk techniques, seniority of the deal, the collateral value, and the value of possible third-party guarantees,
- bank specific characteristics, such as their internal recovery policy and
- exogenous factors, such as the economic environment.

1.3 Exposure at default (EAD)

With regard to Basel Committee on Banking Supervision (2001), EAD is the loss that the bank is exposed to, if the borrower defaults. Crouhy et al. (2001) defines the EAD or the expected loss (hereinafter: EL) as the product of a borrower's exposure, the PD and the borrower's LGD.

EAD is specific for each credit facility. If the company's PD is for example 2%, exposure is $100 and the LGD is 50%, the EAD is calculated as 0.02% x $100 x 0.50 = $1.

According to Treacy and Carey (2000), the EAD or EL is in line with equation 2 below, the product between PD and LGD. Opposite, the unexpected loss (hereinafter: UL) defined in the equation 3, represents the standard deviation of loss or volatility.

$$EL\ (expected\ loss) = PD\ x\ LGD \tag{2}$$

$$UL\ (unexpected\ loss) = LGD\sqrt{PD(1-PD)} \tag{3}$$

The survey of Basel Committee on Banking Supervision (2000) revealed that EAD predictions for facilities with uncertain drawdown were made solely by banks that used a form of capital allocation model. In these cases, EAD was estimated as the sum of committed but undrawn amount and the amount that was actually drawn, multiplied by a factor of "x".

2 RATING SYSTEMS

Banks and credit risk agencies developed rating systems to assess credit risk. According to Grunert et al. (2005, p. 509) rating systems are defined as: "[...] a screening technology that is applied to alleviate asymmetric information problems between borrowers and lenders". According to Saunders and Allen (2002), U.S. Office of the Currency (hereinafter: OCC) is one of the oldest ratings for predicting of borrower's default. This rating system was used by banks and regulators to estimate sufficiency of their loan loss reserves. During the last decades, OCC rating system was extended and replaced by internal rating systems.

When rating a borrower, one have to decide whether to grade it according to its current conditions ("point-in-time"' rating assessment), or its expected creditworthiness over the life of the loan ("through-the-cycle" rating assessment). Rosch (2005) describes that the second assessment is usually performed by external credit rating agencies, while banks mostly applied the first philosophy. Credit rating agencies provide forward looking and long term ratings that target more than one business cycle, but do not offer a picture of the present or near future. Such ratings are almost constant over time and are adapted solely when borrower occur major stress situation that will affect its long term status. Crouhy et al. (2001) argue that credit agencies assess borrower's position at the worst point in a loan cycle. The risk grade is than applied according to that time.

In view of Rosch (2005) on the other hand, a point in time approach, assess borrower's current state and prospects of a near future over pre-specified horizon. Therefore, as soon as the borrower's condition changes, the ranting also changes. Crouhy et al. (2001) argue that, point in time approach is more suitable when the goal is to assign economic capital, set up loan reserves and monitor loans. Main limitation of point in time rating is that such system is more sensitive to change in the credit condition of the borrower. Thus, it has to be updated frequently, which is consistent with the use of ratings as an input to a bank credit model.

Basel Regulation does not propose one rating philosophy over another, when calculating regulatory capital requirements. Rosch (2005) found out that the point in time ratings may be punished under Internal Ratings Based approach (hereinafter: IRB) in economic declines, when borrowers' short term PD increases. This is the case, because Basel Regulation does not take into account lower correlation and lower economic risk that the point in time rating generates.

In the following chapters, I will divide ratings among external, provided by the credit rating agencies and internal ones that are made by banks to asses creditworthiness of their borrowers. Firstly, I will briefly present external ratings and then describe internal ones in great detail.

2.1 External rating systems

External rating systems are provided by different credit rating agencies. According to Saunders and Allen (2002, p. 20), they mainly prepare ratings for countries and companies, mostly for customers, who are bond issuers. Over the years, they also add provision of information via rating reviews and outlooks to their service. Those information give suggestions of future credit ratings developments. Almost all public issues of debt instruments in the USA and Canada are rated by credit rating agencies. Their ratings of public bond issues are publicly accessible and periodically reviewed.

There are several players in the credit rating industry, among others, the most known and influential are Moody's, Standard & Poor's, Fitch and Duff & Phelps. Among them, the most known and quoted are Moody's and Standard & Poor's. However, agencies' rating or opinion about the condition of a company or country can differentiate. Bissoondoyal – Bheenick (2004) argues that Moody's and Standard and Poor's regularly disagree on some particular ratings grades. One example of such a difference happens between the Mexican crises in year 1994. Standard and Poor's gave Mexico a BB+ grade, being optimistic, while Moody's gave Ba. In general, such differences usually appear for low graded countries or companies. That demonstrates how difficult it is sometimes to estimate the credit risk of the entities and the possibilities of their repayment of obligations.

Recently, the usage and the importance of credit ratings have risen considerably. Ratings have impact on issuer's access to capital, cost of capital, structure of financial transactions, regulatory requirements and the capability of entities to make investments. Usage of ratings increased because of better access to information, globalization on financial markets and increased complexity of the financial transactions and products.

The work of credit rating agencies have been criticized frequently in the past. They failed to predict the Asian financial crisis in 1997, the collapse of Enron Corporation and also the recent financial crisis. According to Duff and Einig (2009), the case of Enron was an example that we cannot fully depend only on credit ratings. Four days prior Enron collapse, three major credit rating agencies grant Enron with investment grade ratings. If the critique about the credit rating

agencies' work is more or less legitimate, Duff and Einig (2009) argue that the real concern is in its business model. It is designed in a way that issuers pay for a rating, while the users of the ratings are investors. This creates a conflict of interest. After the recent financial crises, there has been a lot of criticism regarding credit agencies business model in Europe. EU response with new directive and delegation of tasks to European Banking Authority (hereinafter: EBA) together with European Security and Markets Authority and European Insurance and Occupational Pensions Authority. Those tasks being delegated to EBA include promotion of consistent implementation of directives and regulation, especially Capital Requirements Regulation directive (CRR/CRD IV) and European Regulation for Credit Rating Agencies (CRA 3), (European Banking Authority, 2014).

2.2 Internal rating systems

External credit ratings are being used from the beginning of the 20th century, while internal ratings were mainly introduced by banks in the nineties (Grunert et al., 2005). Crouhy et al. (2001) argue that design of internal and external ratings is similar, both consisting from several rating classes. The main difference is that internal ratings are used for classification of bank borrowers and are internal credit risk assessment of bank's clients. Borrowers are ranked into different rating classes and each class represents the borrower's PD in repaying its obligation towards bank. On the other hand, external rating systems, are mostly prepared for customers who are bond issuers. According to Jacobson, Linde and Roszbach (2006), what distinguishes internal ratings from external ones is also the nature of information that internal ratings contain. Banks possess the private information about the borrowers, while credit ratings agencies only use public information.

Treacy and Carey (2000) argue that internal ratings are broadly used in commercial banks. They are not only adopted for assessing company's standing and near future prospects, but also for portfolio monitoring, loan loss reserve analysis, loan pricing, profitability analysis, internal capital allocation and return on equity analysis. According to Basel Committee on Banking Supervision (2000), almost all banks that they surveyed, used ratings to prepare a summary report to senior management and for the pricing analysis. One third of the banks told that in their rating systems, the level of reserves is directly related to the rating classes. It is Basel Committee on Banking Supervision (2000) impression that a reasonable number of the remaining two thirds of banks inevitably look at the rating information, when deciding about reserves. Also very important, almost half of the banks surveyed, consider rating information for allocating economic capital to business lines. Furthermore, the rating process came up to be strongly integrated into the loan approval decisions at almost all bank surveyed. Some of them even clearly noted that loan approval authority is bound with different rating categories.

To derive internal grade to the borrower, ratings consist of financial and non-financial indicators. According to Crouhy et al. (2001), the final grade is based on many characteristics, but it is usually not measured with formal model that would show how to weight all these attributes in a normative way. Ratings are not based on mathematical modelling only, but also

on human experience and judgement. They also contain subjectivity, so they cannot be seen as precise. Crouhy et al. (2001) see the main problem experienced by banks in assessment of credit ratings with obtaining information about companies that do not issue securities. Those companies (usually small and medium sized) are explicitly in need of bank lending if they want to grow. It is difficult for a bank to obtain data about those companies because the quality of data is unproven and consequently less reliable.

When describing the rating systems, Foglia et al. (2001) expressed the components that could differentiate between models: whether the model relies on mathematical techniques or to the expertise of loan officers (or mixture), whether the calculation of PD per grade is made by the model itself or by taking the historical loss experience of the bank's portfolios and whether ratings are established on an facility or obligor dimension. According to Crouhy et al. (2001), facility ratings are combination of PD by the borrower and the loss from the credit facilities available to that borrower. Different facilities that borrower have at bank have different priority rules if the bankruptcy occur. If characteristics of facilities are similar, banks could apply the same rating to each facility.

60% of a 50 large US banks that Treacy and Carey (2000) included in their analysis, had one dimensional rating system, which mean that they use facility ratings. The remaining 40% had system in which PD is assessed on a scale, while the risk applied by individual exposures is assessed on another same number of category scale. In those two dimensional systems, one grade reflects PD and another the EL, which is more precise, because PD and EL are recorded separately. In the Basel Committee on Banking Supervision (2000) survey, the majority of the banks surveyed use ratings that primarily indicate the risk that borrower will default. Approximately 20% of the banks surveyed, use single facility dimension ratings and about one third of the banks make use of a two-dimensional rating system. Two-dimensional rating consists of both an obligor and a facility grade.

According to He et al. (2008), internal ratings during the last years have evolved into diverse and complex systems with large number of counterparties. This is why banks needed to develop their traditional methods, such as the accounting information-based models. Those methods have some major disadvantages. He et al. (2008) argue that their first drawback is their infrequent updating that is being made only once or twice a year. Furthermore, the data that serve as inputs for those accounting-based approaches are released with lime lag, are not updating frequently enough and could also be manipulated because of the conflicts of interest between banks and regulators. In my research I will compare accounting – based approach with the model that includes accounting and non-accounting based inputs.

Due to no strict regulation or empirical evidence about the best rating system practice, the use of internal rating systems raises lots of issues. A number of grades, according to Treacy and Carey (2000), in internal ratings, vary noticeably across banks. Having large numbers of grades in internal ratings is for banks more expensive, because of the extra work needed to distinguish finer degrees of risk. Furthermore, the distribution of portfolio among grades is related to the

size of the bank, the type of the loan facilities and the internal rating model chosen. Many banks have because of that adopted the scale used by the external credit rating agencies, which was also reported in the Basel Committee on Banking Supervision (2000) survey. However, Treacy and Carey (2000) found that banks that changed internal rating model recently, all increased the number of grades. If bank have a big part of its business with large corporate clients, tend to have more grades that more precisely reflects different degree of risk. The banks by the Basel Committee on Banking Supervision (2000) reported that the average number of rating classes is 10. The smallest number of classes reported was 2 and the larges 20.

Jackobson et al. (2006) compared the internal rating systems between the two Swedish banks. Their results showed that the degree of concentration and the distribution of borrowers over rating classes vary widely between low and high risk borrowers. If the presence of concentrations of counterparties in a small number of rating grades is high, the default risk will not be homogeneous within all grades. However, the condition of homogeneousness within all grades is required by regulators.

2.2.1 Rating process

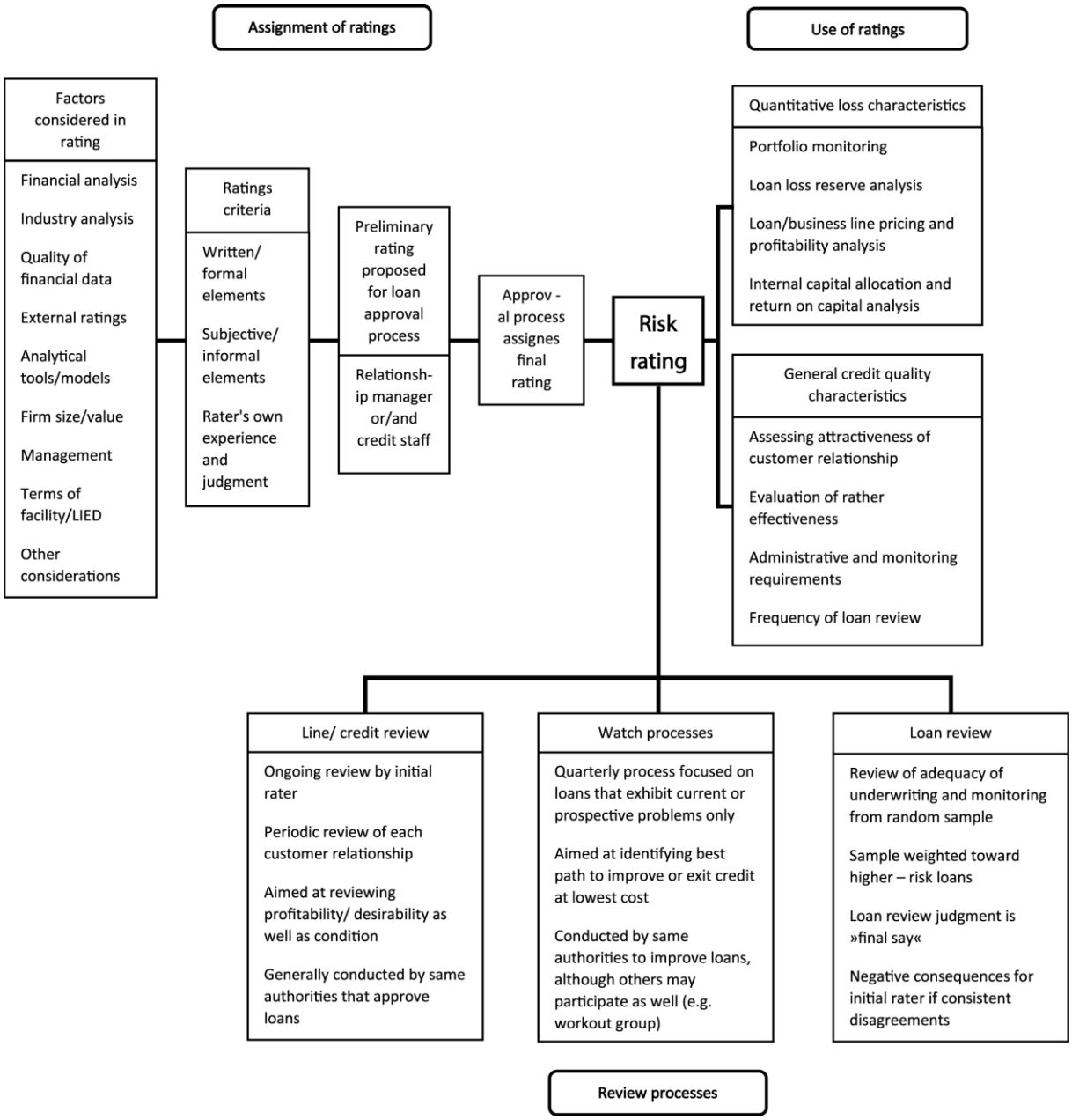
Rating procedure in banks is usually done in a few steps. Crouhy et al. (2001) briefly described that process. Banks first analyze financial reports and examine different financial ratios, than they determine if the cash flows and earnings are sufficient for repayment of debt. Furthermore, they analyze trend of the borrower's business, estimate this trend in the future, assess the quality of the borrower's assets and cash reserves and analyze company's leverage. Analysis of the possible unexpected events' impact is also crucial. Final step is to calculate the ratios that were gathered in the previous analysis and insert them in the model to calculate rating (Crouhy et al., 2001).

Treacy and Carey (2000) describe the rating process with the Figure 1 below, where the process is divided into the assignment of ratings, the use of ratings and the review process. Assignment of ratings in banks comes first. Ratings are assigned based on factors that serve as an inputs for rating model. They are initially assigned by relationship manager (hereinafter: RM) or credit staff. Financial analysis is performed to observe indicators, but banks also have to pay attention to quality of financial data. Information about external ratings, if available, can also be considered. Treacy and Carey (2000) argue that important part of ratings assignment is also company's size and its management. Type of the model or method used, have also been carefully selected. Ratings criteria include written or formal elements as well as subjective or informal elements. Rating usually includes also the human judgement and experience, especially in case of non-financial factors assessment. When the rating is being calculated, it is first "preliminary" or unconfirmed and it is proposed in loan approval process. Assignment of rating is done in the approval process or underwriting action when the rating is reviewed and confirmed by risk management. The number and level of signature of approval typically depend on the size and risk rating of the decision. Performance of the RM is according to Treacy and Carey (2000) usually measured on the basis of the profitability, so the ratings assigned affect

RM compensation. Thus, in the absence of sufficient controls, RM may assign ratings with a manner that is inconsistent with the bank's interests. Credit staff is responsible for approving loans and in 40% of banks, according to Treacy and Carey (2000), also for the review of the ratings assigned by RM.

Figure 1 also shows the use of ratings that I already mention before. In this figure, use of ratings has been divided to quantitative loss characteristics and general credit quality characteristics. Another important role of ratings is also review process that is presented in bottom part of the Figure 1. Ratings are used in review process that includes line or credit review, watch processes and loan review. Line review can be ongoing or periodic and is generally conducted by the same authorities that approve loans. Watch process is made quarterly and is focused only on loans that exhibit current or prospective problems. Their aim is to identify best path to improve or exit credit at lowest cost. Loan review is review of adequacy and is made from random sample.

Figure 1. Risk rating process



Source: W. F. Treacy & M. Carey, *Credit risk rating systems at large US banks*, 2000.

2.2.2 Regulation on internal ratings

Banks are regulated with Basel rules. Currently, Basel II regulation is still valid, however Basel III has to be implemented with phase-in arrangements until the end of 2019. In 2001, the Basel Committee first introduced the IRB approach to capital requirements for credit risk. The important novelty of the approach was that banks were allowed to use their own internal

assessment of their clients and portfolios. Saunders and Allen (2002) describe that the bank which decides to follow IRB approach, have to establish an internal ratings model and classify the credit risk exposure of each on or off the balance sheet facility. There are two approaches under IRB: foundation and advanced approach. For the foundation approach, according to Basel Committee on Banking Supervision (2001), banks input their own assessment of the risk default of the obligor, but estimates of additional risk factors are derived through the application of standardized supervisory rules. Banks can follow foundation methodology if they can prove to supervisors that they meet predefined minimum requirements of their internal rating systems, risk management processes and competence to assess risk components. Advanced methodology on the other hand, allows banks to use their own internal estimations of risk components as PD EAD, LGD and maturity. PD is a main concept on which IRB approach is built. If bank decides for the advanced approach, it has to also meet minimum requirements suitable for foundation approach and also the extra requirements related to risk components. So basic inputs, according to Basel Committee on Banking Supervision (2001), for the IRB approach are the credit risk components (PD, EAD, LGD and maturity) and consequently, capital requirements derived from it. As such, most aspects of the IRB framework are designed to provide confidence that these elements are separately identifiable, measurable and capable of being verified by both, banks and supervisors.

Two key objectives of the IRB approach are additional risk sensitivity and incentive comparability. Additional risk sensitivity could be reached because capital requirements based on internal ratings are proven to be more sensitive to the credit risk and economic loss. Second goal is reached because the appropriately structured IRB approach can provide a framework, which stimulates banks to continue improving their credit risk management. With this approach, committee's objective was to see more banks moving from the standardized approach to the IRB approach and after some time use advanced methodologies. That advanced methodologies will than improve risk management practices.

According to Barakova and Palvia (2014), the IRB approach is quite different than the Basel I, which contain constant risk weights per asset class. Motivation for developments within Basel regulation was to allow banks more discretion in assessing risk. Therefore, substantial differences in IRB parameters and risk weights across banks are expected and if banks estimate risk accurately, such differences should be primarily driven by the riskiness of bank loan portfolios. But which approach is better? Barakova and Palvia (2014) documented stronger correlations of loan performance measures with Basel II/III risk weights than with Basel I risk weights. However, there are few concerns regarding IRB approach that I would like to mention. Since internal ratings influence on minimal capital requirements, banks can manipulate the system without sufficient supervision, especially if banks view capital as costly and wish to minimize the cost. Barakova and Palvia (2014) also mentioned that financial markets do not have a complete trust in the new Basel risk weights. Basel Committee in response issued a report where they find that there are important drivers that provide risk weighted assets (hereinafter: RWA) variation and that these drivers are practice-based (Basel Committee on Banking Supervision, 2013). These drivers are different approaches (IRB or advanced IRB)

conservativeness of adjustments to different approaches' parameter estimates and different models applied. According to Basel Committee on Banking Supervision (2013), LGD estimation appears to be a significant source of differences in RWAs under the Advanced IRB across banks.

2.2.3 Role of ratings in loan approval process

Ratings have an important role in commercial banks, not just to calculate the regulatory capital, but also to decide on loan approvals. To find out more on that issue, I made an interview with the Head of Risk Management Department in one of the Slovenian banks. In the interview, I asked about the importance and usage of internal ratings in decision making process and also about different indicators that are important when assessing credit risk. I will mention different indicators in the chapters later on.

For loan approval decisions, company's rating is used like a tool for decision making. It is used more as additional information about the borrower, not the core information, on which the decision is based. This is the case because in rating models, there are not all important indicators included, otherwise the models would be too complicated. On the other hand, risk managers have to consider all information available. Nevertheless, ratings are very important in commercial banks, because they have a great influence on the banks' balance sheet, through the calculation of bank's capital. In risk manager's opinion, the decision upon loan approval should never be based solely on ratings, because it is not possible to develop that kind of model that will replace human judgement and be more successful when assessing risk. Models can also be manipulated, especially if a loan officer has an interest to present the company in a better light as it is, since it is usually paid according to the sale of loans. That is why it is important that loan officers are controlled by the risk managers. In practice, this rule is usually realized in a way, that loan offices are responsible for non-financial indicators collection and risk managers than control the answers and confirm the accuracy of the rating grade. However, loan officers are usually also the one that provide information about the company to the risk managers, which can sometimes lead to insufficient control. This happens because risk managers sometimes cannot control the facts which are not publicly available. In the next chapter, I will present different indicators that are included in rating models.

3 INTERNAL RATING INDICATORS

Internal ratings in commercial banks consist of several indicators that serve as an input for rating models. When designing a rating model, banks need to decide, which attributes have to be taken into account and what weight have to be applied for each of them. Bessis (2002) for example, divides rating criteria into qualitative and quantitative variables, where quantitative variables are mostly financial variables. I will divide different indicators into financial and non-financial and present them in the following two chapters.

3.1 Financial indicators

It is difficult to say, which financial ratios best estimate company's PD and have to be included in the rating systems. Some financial ratios are also quite similar and have high correlations among each other. However, in the literature, we can find some suggestions which indicators tend to be the most important.

Crouhy et al. (2001) concentrate on the three main financial assessment areas that have to be analyzed when assessing PD: (1) earnings and cash flows, (2) asset values, liquidity and leverage and (3) financial size, flexibility and debt capacity. Typical ratios representing each of those areas are according to Crouhy et al. (2001):

- Ratios that describe interest coverage: Earnings Before Interest and Taxation (hereinafter: EBIT)/interest expense or Earnings Before Interest Taxation Depreciation and Amortization (hereinafter: EBITDA)/interest expense
- Ratios that describe leverage: current ratio (current assets/current liabilities) and total liability/equity
- Indicators that describe what the access to capital markets is for a certain borrower: the phrase "access to capital markets" refers to the demonstrated or potential near-term ability to issue public securities. For private or smaller companies, analytics have to consider the ability to access these markets.

Aside the three main assessment areas, Crouhy et al. (2001) also highlighted the following ratios as one that are the most important: funds from operations/total debt, free operating cash flow/total debt, pre-tax return on capital, operating income/sales, long term debt/capital and total debt/capitalization. Orsenigo and Vercellis (2013) determined that key financial variables in internal rating models are: return on average equity, cost to income ratio and loans on total assets. Grunert et al. (2005) in their research on the role of non-financial indicators in internal credit ratings used following financial indicators: logarithm to total assets, equity to assets ratio, current ratio, cash flow to net liabilities, capital intensity ratio and return on assets (hereinafter: ROA). Bessis (2002) provides a framework of financial criteria applicable to all borrowers, which is presented in the table below. He divides financial ratios based on the nature of variable.

Table 1. Financial criteria applicable to all borrowers

Nature of variable	Measures
Size	In terms of total assets, or sales or profit measures such as EBITDA or net income
Operating profitability	Operating return (before interest, amortization and taxes) on assets, Operating margin or operating profit/sales
Financial profitability	Return on equity (hereinafter: ROE), net income over equity
Financial structure	Debt to equity structure, debt/equity (usually only on financial debt) Debt structure or senior debt to subordinated debt Financial coverage ratio such as EBITDA/interest
Cash flow	Operating cash flow or free cash flow
Operating efficiency	Inventories turnover Receivables in days of sales Payables in days of purchase Net cash cycle
Operating leverage	Ratio of direct and variable cost to fixed cost
Liquidity	Short term cash and investment over total assets Current ratios and other variations
Market value	Equity to book value Price to book value
Volatility of earnings and sales	From time series of sales and profit

Source: J. Bessis, *Risk Management in Banking*, 2002, p. 448.

At the Slovenian market, one of the newest research on different indicators for rating companies, was made by Volk (2012), who analyzed Slovenian non-financial companies. He found that the most important financial indicators for rating companies are total sales, quick ratio, debt to asset ratio, ratio between operating cash flow and revenues and asset turnover. According to Volk (2012), total sales have a negative coefficient, which can be interpreted that larger companies have a lower PD. Similar is for companies with higher liquidity (indicators used was quick ratio), since the analysis showed that they have also lower PD. Volk (2012) argue that defaulted companies in theory are expected to have more debt or higher leverage. The negative sign of debt to assets ratio in his model proved that. Cash flow displays a negative coefficient. It is expected that companies that are stable, mature and profitable produce sufficient cash flows to pay off the owners and creditors. Asset turnover ratio in Volk's (2012) research indicates that more efficient companies default less often.

When deciding on importance of each ratio, Crouhy et al. (2001) argued that there is no general rule which weight to apply to which indicator or sets of indicators. The decision of weighting

should be rather based on the borrower's industry. In the end, what is essential for the final decision? The answer is more or less good judgement.

3.1.1 Analyzing borrower's financial indicators

To find out which of those ratios are mainly used in banks when assessing company's PD or deciding to grant a loan to a potential borrower, I made an interview with the Head of Risk Management Department in one of the Slovenian banks. I asked which items of financial statements or financial indicators are in that particular bank usually analyzed first when assessing credit risk and thus are the most important. According to the risk manager, one must pay attention to:

- Change in inventories

Change in inventories affects profit and loss account through the revenue, but do not have the influence on the cash flow. This item of profit and loss account can improve success of the company through their financial statements, however situation in the reality can be different.

- All revenues that have label "other"

Those revenues are exceptional and increase EBITDA and company's profit. However, these kind of events are unique and are not based on cash flow.

- Current ratio

Current ratio divides current assets with current liabilities. Similar ratio is also the one that compares fixed assets with long term liabilities. The rule of matching liabilities maturity (duration) with maturity (duration) of assets that can be seen through that ratio is very important, however it was neglected in banks in the past years. Many companies in Slovenia are now in big trouble because they have not followed that rule. As an effect, companies' nowadays have many short term loans and are faced with the problem of refinancing those loans. So this rule is not only important in theory, but also in practice.

- EBITDA/ NET DEBT

This EBITDA/ NET DEBT ratio is widely used is banks, however risk managers have to pay attention to content of EBITDA – if it is really a cash flow. EBITDA is a resource for all investments in the company, also for the repayment of principal and interest rates, so for banks, it is a very important item of the profit and loss account.

- CAPEX (capital expenditure)

This ratio tell us how much each company spends for investments in fixed assets.

- Accounts receivable and accounts payable turnover

When assessing accounts receivable or accounts payable, the content can be more important than the number. Risk managers have to analyze, how much receivables are due and how much

of them will not be repaid. Eventually, a company has to write off the receivables that will not be repaid and that have an influence on the profit.

- Accounts receivable to accounts payable

It is a good thing if a company has more receivables than payables, however one has to be careful in identification of the quality of the receivables, as I have already mentioned before. This is also one of the limitations in ratings, because models took all the receivables, despite of the fact that some of them should be written off or will be written off in the near future.

- Financing of inventories

It is very significant how inventories are financed, because they should not only be financed with short term liabilities but also with long term, especially in industries that have a long business cycle.

- Equity to total assets

Equity is the measurement of the company's stability. If a company has taken a non-profitable project or made a wrong business decision, it will survive and stay on the market only if it has enough equity that could absorb the losses. Equity acts like a reserve or a buffer when losses occur.

- Goodwill and financial investments in general

The content of those items of balance sheet is important (same as at accounts receivable), because write offs reduce the assets and influence on the level of equity.

However, there are not only ratios that are important, but also balance sheet and profit and loss account changes, comparing with the past years. This is why risk managers are always comparing yearly and mid yearly financial statements of a company with previous years. Evaluating dynamics of the company's business is essential and risk managers have to pay attention to any deviations from previous years on one hand and stability of the company's operations on the other.

3.2 Non-financial indicators

When analyzing borrowers, the qualitative assessment is usually made as well. How much non–financial indicators contribute to the accuracy of default predictions is the main topic of my master thesis. Non-financial indicators are also called soft indicators, because they are not as straightforward as financial statements or accounting data and always include human judgement. That is why they are subjective and the risk management needs to pay attention to the right assessment of the non-financial indicators. Gurnert et al. (2005) argue that the basis for non-financial indicator choice is usually judgement of experts or common industry knowledge. However there is a lack of research on how much those indicators add to the correctness of the rating system model or to the right assessment of the borrower's quality. That was also a motivation for my research later on. According to Volk (2012), banks could gather

additional non-financial information about the borrower with having close relationship with them. These information are quite valuable when estimating company's creditworthiness.

Besis (2002) expresses the following non-financial indicators as being crucial for driving a company's health: industry, competition, market share and size, diversification of products and services also across countries, growth potential, technology, quality of products and services, management quality and barriers to entry. Volk (2012) found that one of the important indicators is also a company's age, because young companies tend to default more often, since they are more sensitive to different shocks. He added that good indicator is also the one that measure a number of days a company has blocked a bank account per year.

Crouhy et al. (2001) divide non-financial indicators in seven categories and describe them as follows:

- Day-to-day account operations, management quality and concern for the environment

When assessing a borrower, one must check how well is company managed. One have to also check what is the quality of its explanations and data provided. Especially important is the quality of financial reporting and occurrence of any possible delay with financial reporting. Furthermore, one has to assess how well the variations from projections are explained and if the limits and terms were respected. Management quality contains the sufficiency of management skills, ability to identify and manage risks that arise and concern for constant development, including development of new technologies and updating methods. Management also have to address problems immediately and take hard decisions when necessary. Company need to have reasonable business and financial plan and one have to assess if the assumptions are realistic, particularly about the growth and profitability. There are also environmental risks that one has to take into account. These are especially the compliance with all environmental rules, necessary permits and good practices. Banks have to pay attention to all those areas, since several warning signals could appear. In the end, one has to assess if any restructuring have happened in the company during last years.

- Type of industry and the relative position of the borrower within their industry

Industry is an important non-financial indicator, since experience has shown that poorer companies in vulnerable industries contribute to many credit losses. Another important characteristic is competitiveness within the industry. Competitiveness is potential of the industry to generate sales on domestic and external markets, given its cost structure, international reputation and capability in targeting market niches. Regulatory framework of the industry, that includes regulations, laws and subsidies, is also important. Impact of supply, demand, policies and trends has to be considered when making market analysis. Company have to adapt to new technologies that could change cost structure as well as the macroeconomics environment that is constantly changing.

- Importance of the quality of the information provided by the company

The bank has to be fully satisfied with the financial statement information provided in terms of the quality, adequacy and reliability.

- Country risk

Country risk is the risk that a counterparty, or borrower, will not be able to pay its debt, because of currency risk and the political and economic risk of a country.

- Third-party support

If in transaction the guarantor is presented, banks have to assess if the third party/owner is going to provide ongoing support through the whole maturity of facility. If the guarantor will issue warranty, bank has to check if guarantor has adequate funds to repay the debt if obligor defaults. Quality of the third party influences on rating.

- Risk associated with longer-term facilities

Longer term facilities are more risky because it is difficult to estimate the creditworthiness in the future. The lending purpose and structure of the facility have impact on the possibility of not returning the debt.

- Presence of security

Presence of security heavily affects LGD as already mentioned in the LGD chapter. In case of default, there is always a risk of the proper finalization of security (documentation risk) and this risk should be taken into account when assessing the level of protection.

3.2.1 Analyzing borrower's non-financial indicators

Similar to the financial indicators presented before, I also collected some primary data on non-financial indicators through an interview with the Head of Risk Management Department. Non-financial indicators are variables that are gathered in banks from different data bases, media or directly from the borrower. In rating models, non-financial indicators are usually set in general, although sometimes we cannot compare different industries or activities through the same non-financial variable. There are many non-financial indicators that are important when assessing credit risk. According to the risk manager, non-financial indicators that are usually analyzed in banks are:

- Number of days that a company has blocked bank accounts

This indicator is almost the first one that risk managers look at when analyzing credit risk. It is the first signal of how well a certain company is operating.

- Delays in repayments of other bank loans that can be seen in the interbank system.

Those delays in repayments are another good signal of company’s operations and show a repayment discipline.

- Borrower’s relationship with the bank and repayment of the bank's loans

The borrower's relationship with the bank and repayment of the bank's loans or in general, all the company's history with the bank is very important, because the bank can therefore assess the risk better if knowing the company for a longer time.

- Organizational structure

It was proven many times in practice that organizational structure and credit risk are connected. If organizational structure is complicated and the company does not have different activities, there is always a risk involved that company hides something. Otherwise, why would a company take additional cost with preparing financial statements and all documentation for different companies in organizational structure?

- News in media and articles in newspapers

News in media and articles in newspapers are important signs that can reveal many qualitative information about the company.

- Company's industry and market

Risk manager has to assess the prospect of the industry and company's location to get the idea how well the company will operate in the future.

- Identifying the successor

For smaller companies, identifying the successor is crucial. Many times, a company is dependent on one person and everything can change if that person is gone.

- Willingness of providing personal guarantees

Taking responsibility for the leadership decisions in the company can be seen also through willingness of providing personal guarantees. If the owner or Chief Executive Officer (hereinafter: CEO) provides personal guarantee, he is also more motivated to solve problems when they arise.

- Competition within the industry

Not only industry, but also the company's position within the industry and competition are crucial when assessing risk. Company's potential to increase the market share can generate more revenues and it is crucial for company's success.

- Strategy for the future and cash flows predictions

Risk manager argues that cash flow assumptions are not the most important decision or rating indicator, as it is practice in some banks. More important is company's history and its past decisions. This is also the case due to the uncertainty about the future and the possibility of manipulation of the assumptions provided by the company. The company can in cash flow predictions write about the future growth and sometimes it is difficult to check whether the plans are realistic. Also, any forecast making for a longer period of time is usually difficult.

3.2.2 Academic research on non-financial indicators

Despite there is a lack of academic research on non-financial indicators inclusion, there has been few researches and surveys made about the use of non-financial indicators in banks.

Grunert et al. (2005) analyze data from four major German banks and find evidence that the combined use of financial and non-financial indicators leads to a more precise prediction of company's default than the single use of each of these indicators. They found that banks, included in the sample, mainly use two non-financial indicators: management quality and market position. Ciampi (forthcoming 2015) analyzed the Italian small enterprises (hereinafter: SE) defaults and included some corporate governance variables. He found that variables CEO duality (CEO also holds the position of the chairman of the board), owner concentration and a reduced number of outside directors on the board (no more than 50%) are negatively correlated with SE default. Moreover, their inclusion significantly improves the SE default prediction accuracy rates. CEO-duality leads to a more authoritarian leading style by the CEO, lower levels of control, over-concentration of decision-taking functions, a tendency by CEOs to maintain the status quo, and incomplete company's competence to adapt. Ownership concentration is negatively correlated with SE default, because the existence of a mass of shareholders guarantees stability and lowers conflicts between owners (Ciampi, forthcoming 2015).

Treacy and Carey (2000) also found that majority of banks using internal rating systems cite the borrower's management as an important indicators when assigning the credit risk grade. This kind of assessment can reveal lack of management skills, not enough experience and competence, insufficient succession plans and low integrity. Some institutions that were included in their research, weighted this indicator extremely high. They assess also management willingness and ability to lead a company, as well as its attitude of preserving interest of lenders. Among the banks surveyed, borrower's country also has an important position within non-financial indicators. The practice is that borrower's grade is not less risky (higher) than the borrower's country grade (Treacy & Carey, 2000). Basel Committee on Banking Supervision (2000) found that banks surveyed, vary in giving importance to non-financial indicators. Some rely on the non-financial versus financial indicators from 60% or more, but some include small number of non-financial indicators to their internal systems. Berger, Miller, Petersen, Rajan and Stein (2005) found that small banks are capable to better use the gathered information on non-financial indicators than large banks. The reason lies in the fact that small banks have usually closer relationship with their clients and thus better knowledge of them. Moreover, they are usually also present in local environment, where the access of borrowers' information is better. One might think that banks are thus willing to finance higher risk borrowers if they have a close relationship with them. According to Volk (2012), this is not the case in Slovenia. He found that companies in default, have on average higher number of banks working with. In his opinion, the reason might be in the fact that risky companies with poor financial statements seek loans in other banks, because current creditors refuse to lend them, if they are not paying off the loan regularly. In general, the borrower's credit history is not accessible to new creditors, however in Slovenia, banks can see the delays of repaying bank loans in the report of the interbank debt.

4 INTERNAL RATING MODELS

To calculate internal credit ratings, banks use models that are usually mathematical and quite complex. However, Basel Committee on Banking Supervision (2000) found that in rating systems, personal experiences play an important role and they were also a factor in developing and implementing many models and in constructing their inputs. To construct a model, according to Basel Committee on Banking Supervision (2000), a bank first recognizes the financial indicators that seem to provide information about default's probability. Banks with a use of historical data, are estimating the impact of each of these variables on the likelihood of default across a considered sample. These estimated ratios are then adapted to data for current loans. Score that they get is indicating PD and is converted into a rating grade.

Saunders and Allen (2002) define four classes of models for credit risk measurement:

- Expert systems

In an expert system, the loan approval decision is in hand of risk manager, local or branch leading officer or a relationship manager. Most important determinants in the loan approval decision are this person's expertise, subjective judgement, and weighting of particular key variables. One of the most usual ways is that the expert assesses five key indicators, weights them on behalf of his/her experience and make a credit decision. Those indicators are:

- Character: this is a measure that shows company's reputation and the willingness of the company to repay its debt.
- Capital: represents the equity to debt ratio (leverage) and owner's contribution. Low amount of equity regarding debt suggests a greater PD.
- Capacity: shows the volatility of the borrower's earnings and is the capacity to repay debt. If the repayments are constant over time but earnings are volatile, the company's repayment ability is constrained.
- Collateral: is the security that bank having if company defaults. Exposure risk of the loan is low, if the market value of the collateral in time of default is high.
- Cycle conditions*:* the state of the business cycle is important especially for industries that are dependent of the cycle.

- Neural networks

Many systems took the expert's decision and integrate it in the model. Despite these systems can be quite precise, time and effort is needed to convert the human's decision process into a system of rules. There are also difficulties and costs associated with programming the decision algorithm and maintaining the system. Artificial neural networks have been proposed as solutions to these problems. They simulate the human learning process, so the system learns the nature of the relationship between inputs and outputs by repeatedly sampling input/output information sets. That kind of systems are programmed in a way that can make an "educated guess", same as would a human expert do. According to Tu (1996), another advantage of neural

networks is that they are not constrained by a predefined mathematical relationship between dependent and independent variables, and have the ability to model any arbitrarily complex nonlinear relationships.

- Rating systems

Rating systems are in banks in use since the OCC system that was one of the oldest. Over the years, bankers improved their rating systems, especially with introducing Basel IRB approach. More about rating systems was already written in special chapter.

- Credit scoring systems

These systems pre-define particular key variables that determine PD and combine them into a quantitative score. Sometimes that score can be interpreted as a PD, but in some cases the score can be used as a classification system. Classification system places a potential borrower either into a good or a bad group (healthy company or company in a default), based on a score and cut-off value. There are four methodological forms of multivariate credit scoring models: the linear probability model, the logit model, the probit model and the discriminant analysis model. I will describe these four methods in the next chapter.

4.1 Methods for predicting borrower's default

In general, among banks using internally-developed models, according to Basel Committee on Banking Supervision (2000), the modelling technique was most often described as discriminant, logit-based, or classic credit scoring technique. I will present the approaches to analyze two groups of borrower's next: linear probability model, the logit and the probit model. I will also describe the discriminant analysis that I used in my research.

4.1.1 Linear probability model

Gjurati (2003) emphasized that linear probability model used to be applied quite extensively due to its simplicity. Afterwards the computer packages for logit and probit models (that are going to be discussed later) appeared, so now days linear probability model is not that frequently using anymore. Equation 5 below represents linear probability model (Gjurati, 2003) in which for example, X means family income and Y = 1, if the family owns a house and Y = 0, if it does not own a house. This equation represents classic regression model, however, because the regressand is dichotomous, it is called a linear probability model.

$$Y_i = \beta_1 + \beta_2 X_i + u_i \qquad (5)$$

According to Gjurati (2003), this is because the conditional assumption of Y_i given X_i, E (Y_i | X_i), can be explained as the conditional probability that the event will happen, given X_i, that is, P_r ($Y_i = 1 \mid X_i$). If P_i is probability that $Y_i = 1$ (that is, the event occurs), and $(1 - P_i)$ is probability

that $Y_i = 0$ (that is, that the event does not occur), the variable Y_i has the Bernoulli probability distribution.

However, linear probability model has several limitations. Gjurati (2003) mentioned four of them: (1) non-normality of u_i, (2) heteroscedasticity of u_i, (3) possibility of Y_i lying outside the 0–1 range, and (4) the generally lower R^2 values. Some of these limitations could be resolved with different methods. For example, one can use weighted listed squares to solve the heteroscedasticity problem or increase the sample size to minimize the non-normality problem. By applying mathematical programming techniques, one can even make the estimated probabilities lie in the 0 – 1 interval. Basic problem with linear probability is for Gjurati (2003) the fact that the model assumes that $P_i = E(Y = 1 \mid X)$ increases linearly with X. This means that the marginal effect of X stays constant throughout. In example of owning or renting a house, when X increases by a unit (for example $1000), the probability of owning a house increases by the same constant amount of for example 0.10. This is the case, whether the income amount is $8000, $10,000, $18,000, or $22,000, which it seems illogic. In research area, that gave popularity to the logit and probit model that I will describe next.

4.1.2 Logit model

Gjurati (2003, p. 595) defines the logit model as: "Logit model is a technique, which allows estimating the probability that an event occurs or not, by predicting a binary dependent outcome from a set of independent variables". According to Gjurati (2003, p. 595), the logit or logistic model is set by logistic distribution function written in equation 6 below, where $Z_i = \beta_1 + \beta_2 X_i$ and ranges from $-\infty$ to $+\infty$. P_i lies between 0 and 1 and is nonlinearly connected to Z_i (i.e., X_i). The difference between the linear probability model described before and the logit model is that the linear probability model estimates that P_i is linearly related to X_i, while the logit model assumes that the log of the odds ratio is linearly related to X_i.

$$P_i = \frac{1}{1 + e{-}Zi} = \frac{e^2}{1{+}e^2} \qquad (6)$$

However, with the formula above, the estimation problem is faced, because P_i is nonlinear in the β's (not only in X). This means that one cannot use the ordinary least squares procedure to assess the parameters. Fortunately this problem can be solved, because it can be linearized, which is shown in the equation 7 (Gjurati, 2003, p. 595). Gjurati (2003) argues that if one takes the natural log and obtains L, the log of the odds ratio, that is not only linear in X, but also (from the estimation viewpoint) linear in the parameters. L in equation 7 below is called the logit so the name for the model below is logit model.

$$L_i = ln\left(\frac{Pi}{1-Pi}\right) = \beta_1 + \beta_2 X_i + u_i \qquad (7)$$

According to Gjurati (2003, p.596), more formally, the interpretation of the logit model is as follows: "β_2 (the slope) measures the change in L for a unit change in X, that is, it tells how the

log-odds in favour of owning a house change, as income changes by a unit. The intercept β_1 is the value of the log-odds in favour of, for example, owning a house if an income is zero."

4.1.3 Probit model

Probit and logit models are quite similar. According to Gjurati (2003), the main difference between them is that the logistic distribution has slightly fatter tails. Probit or sometimes called normit model according to Gjurati (2003), arrives from the normal cumulative distribution function. It is a type of regression or a probabilistic statistical classification model, where the dependent variable is binary. The decision mentioned before about the owning the house or not, rely upon on an unobservable utility index I_i (also known as latent variable), that is presented by one or more descriptive variables (say income X_i) in such a way that the higher the value of the index I_i, the greater the probability of a family owning a house. Gjurati (2003, p.608) expresses the utility index I_i as in the equation 8 below, where X_i is the income of the i-th family.

$$I_i = \beta_1 + \beta_2 X_i = F{-}1(I_i) = F{-}1(P_i) \qquad (8)$$

Gjurati (2003) argues that now one could assume that there is a critical level of the index, call it I^*_i, such that if Ii exceeds I^*_i , the family will own a house, otherwise it will not. Although the threshold I^*_i (like I_i) is not observable, it is assumed that it is normally distributed with the same mean and variance. This is why, it is possible to get some information about the index itself, not only to estimate the parameters of the index given in equation 8. Given the assumption of normality, the probability that I^*_i is less than or equal to I_i, can be computed from the standardized normal cumulative distribution function. If one wants to obtain information on the utility index and on β_1 and β_2, the inverse of equation 8 has to be applied. In this equation, F−1 is the inverse of the normal cumulative distribution function.

4.1.4 Discriminant function analysis model

Discriminant analysis is a method that statistically distinguishes among two or more groups of units (Beharav & Nevo, 2003). These groups are defined by the particular research situation, in case of internal ratings, by defaulted or non-defaulted companies. Researcher selects different discriminating indicators that measure aspects, by which the groups could differ. Rovan (2014) described that the goal of discriminant analysis is setting discriminant function and based on its values, separate groups of units in a maximum way possible. Optimal linear combination of variables is the one that maximizes the square between the group's averages, divided by the total variance in groups. According to Altman (1968), discriminant analysis is a statistical technique, used to classify an observation into one of several priori groupings, dependent upon the observation's individual attributes. It is usually used if the dependent variable appears in qualitative form. First, researcher has to establish group classifications and in second step, collect and calculate data for the units in each group.

The discriminant function is presented by R.A. Burns and R.B. Burns (2008) in the equation 9 below. This equation shows how discriminant function transforms individual variable values to a single discriminant score (D value) that is then used to classify the object. Weights or ratios for variable (V_j) are being computed and the independent variables (X_j) present the actual values or company's scores. Good predictors tend to have large weights and as I have already mentioned before, the researcher wants to set up an equation that has a strong discriminatory power between groups. R.A. Burns and R.B. Burns (2008) argue that after using an existing set of data to calculate the discriminant function and classify cases, any new cases can then be classified.

$$D = v_1X_1 + v_2X_2 + v_3X_3 + \ldots\ldots + v_iX_i + a \qquad (9)$$

According to Altman (1968), when observing a lot of financial ratios in assessing a company's bankruptcy potential, there is a chance that some of the measurement will have a high degree of correlation with each other. This is one of advantages of the discriminant function model, because one can yield a model with a relatively small number of measurements. Those measurements have then the potential of explaining a great deal of information. However, variables need to be selected carefully. Information gathered might very well indicate the differences between groups, but is it also important if these differences are significant and meaningful. Altman (1968) argued that the primary advantage of discriminant analysis is the potential of analyzing the entire variable profile of the object at one time, rather than separately examining its individual attributes.

According to R.A. Burns and R.B. Burns (2008, p. 591), there are several purposes of discriminant analysis. Fist, one could investigate the differences between groups on the basis of the attributes of the cases, indicating which attributes contribute most to group separation. The descriptive technique identifies the cannonical discriminant functions, which contribute maximally to group separation. The discriminant analysis function produces scores on the predictor variables to predict the category, to which the unit belongs. Secondly, one could determine the best way to distinguish between groups. Thirdly, one could classify cases into different groups. A statistical significance test enables to see how well the function separates the groups. In addition, with discriminant function analysis one could test the theory whether cases are classified as predicted.

Discriminant analysis as any other analysis has some limitations. Uddin, Meah and Hossain (2013) listed four of them:

- Equal variance – covariance matrix

The main assumption to apply the discriminant analysis is that the groups have equal variance-covariance matrices, although their means are substantially different. This assumption is tested with a transformed value of Box's M. If the problem of equal variance-covariance matrices is violated, the solution could be the sample that is large enough.

- Multivariate normality

An important assumption of estimating discriminant analysis is that all of the groups in the dependent variable are selected randomly from a multivariate normal population. To test this assumption, normality test of the variables can be conducted using a histogram with a normal curve.

- No multicollinearity

There should not be multicollinearity in the independent variables. To check the assumption of multicollinearity, the correlation matrix can be used. The multicollinearity problem can be solved by using a stepwise discriminant analysis, however if multicollinearity is found in the data, it should be corrected.

- Linearity

Unlike regression analysis, in discriminant analysis, the dependent variable is non-metric. Consequently, there is no linear relationship between dependent (non-metric) and independent (metric) variables. But between the independent variables, the linear relationship is required.

According to Uddin et al. (2013), discriminant analysis is widely used particularly for insolvency prediction, and sales force turnover management. If comparing it to the other methods, the advantage is in their simplicity, but it can still explain a great deal of variability. According to Altman (1968), one can yield a model with a relatively small number of measurements that can cover a great deal of information due to correlation. Another advantage of discriminant analysis is that it considers an entire profile of characteristics common to the relevant units, as well as the interaction of these variables and that it reduces the analyst's space dimensionality. Discriminant analysis also has the potential of analyzing the entire variable profile of the object simultaneously rather than sequentially, examining its individual characteristics (Altman, 1968). Furthermore, Cox and Wang (2014) used discriminant analysis in predicting the US bank failure and argued that discriminant analysis has the statistic ability to reduce the chance of type 2 errors.

Disadvantages of the discriminant analysis were already presented as limitations. Some of them could be overcome with different assumptions or corrections. According to Cox and Wang (2014), the main disadvantage of discriminant analysis is the assumption of the normal distribution. Because of that, discriminant analysis is sometimes replaced by logistic or logit regression that do not assume normally distribution and equal within group variance matrices. Li, Sun and Yan (2013) in their work about forecasting business failure used multivariate discriminant analysis and logistic regression and proved that if comparing both models, logit model is more flexible in its assumptions.

Since the probit model is similar to logit model, which of them is preferable? According to Gjurati (2003), as mentioned before, the logistic distribution has fatter tails. This means that conditional probability approaches zero or one at a slower rate in logit than in probit. However,

Gjurati (2003) argues, that there is almost no reason to choose probit over the logit. In practice, because of its mathematical simplicity, many researchers choose the logit model.

5 ANALYSIS OF PREDICTING BORROWER'S DEFAULT BY FINANCIAL AND NON-FINANCIAL INDICATORS

5.1 Methodology

According to Blochlinger (2012), two characteristics of a good credit risk model are discrimination and calibration. When predicting borrower's default, discrimination represents the model that distinguishes well between defaulted and non-defaulted borrowers. Calibration means that the model match actual and predicted values, across the entire set of the information. Good calibration is demonstrated, if the number of companies in default align well with the number of predicted defaults by the model. In my empirical research, I will investigate several ratios and try to find that kind of multiple discriminant function that will have the best discrimination and calibration.

5.1.1 Research design

To answer the research question and verify a hypothesis, I decided to apply the discriminant function analysis. I've chosen this method because it is simple, but still explains a great deal of variability. It also reduces analyst's space of dimensionality and covers a great deal of information with a small number of variables, due to their correlation. The sample criteria used is going to be described in the next chapter. The financial ratios were calculated from each company's accounting statements that are available for all Slovenian companies at Agency of the Republic of Slovenia for Public Legal Records and Related Services (AJPES) and non-financial indicators chosen, are available at database GVIN. Indicators that serve as an analysis' inputs are going to be described in the next chapters. I made different versions of discriminant functions to see the difference between applying solely financial and both financial and non-financial indicators. Additionally, Uddin et al. (2013) argue that discriminant analysis is very outlier sensitive. This is why, outliers should be identified and excluded from the analysis. So I dropped all the observations that lie outside the three standard deviations and made additional two versions. When eliminating outliers, SPSS gave us two options: replace the eliminating units by variables mean value or exclude the units from the analysis. To see how the different method influence the results, I applied both. All versions and their characteristics are presented in the Table 2.

Table 2. Data for different versions

Type of version	Type of indicator	Type of data	Type of method in SPSS	Number of units observed
Version A	Financial	All data	-	80; equally large groups
Version B	Financial	Elimination of outliers	Replaced eliminated outliers by variables' means	80; 20 units were replaced by mean, equally large groups
Version C	Financial	Elimination of outliers	Compute from the group size	60; 20 units were eliminated, group of default had 27 units, group of non-default had 33 units
Version D	Financial and non-financial	All data	-	80; equally large groups
Version E	Financial and non-financial	Elimination of outliers	Replaced eliminated outliers by variables' means	80; 35 units were replaced by mean, equally large groups
Version F	Financial and non-financial	Elimination of outliers	Compute from the group size	45; 35 units were eliminated, group of default had 26 units, group of non-default had 19 units

5.1.2 Sample structure and criteria for inclusion

To form a sample, I decided to choose 80 companies, 40 of them in group of default and 40 in group of non-default. To satisfy the criteria to have homogenous groups, I decided to include Small and Medium-sized Enterprises (SMEs) only and within SME definition, I also shrank the sample based on company's yearly sales. For the definition of default, I took the state when a company is in bankruptcy. The sampling method I have chosen is random sampling, which was designed in a way to randomly choose companies from the random list that was prepared by a computer from the database. Next, I will briefly present the argumentation for choosing that criteria.

5.1.2.1 Criteria for including units into the sample

I used a sample of 80 companies for my analysis, excluding non-profit companies. I chose 40 companies that were in bankruptcy, according to Slovenian legislation at the time that the research was made and another 40, which were active at the market. I concentrated on small and medium-sized enterprises. Those companies play fundamental roles in most economies; in Slovenia, according to Evropska komisija (2014), there was 7,577 small and medium sized enterprises (hereinafter: SME), which represents 7% of all companies at the market (micro companies represent 92.8% and large companies represent 0.2% of the Slovenian market). SMEs in 2012 produced most added value (40.9%), when micro companies produced 22.1% and large 37% added value. Furthermore, SMEs companies employ most workforce in Slovenia, in 2012, there were 40.1% of all working force employed in SMEs, when in micro

30.5% and in large 29.5% of all active workforce. We can conclude that SMEs are very important for the Slovenian national economy.

If SMEs want to grow, they usually need external funding, because the equity market for such is not very well developed. Furthermore, issuing securities is for SMEs often very costly and ineffective. SMEs also often lack financial knowledge from a specialist, who will help with issuing equity at financial markets. That is why such companies often rely on commercial banks, when need financing. Gama and Geraldes (2012) argue that on the other hand, banks are skeptical to lend to SMEs, because for such companies there is a lack of publicly available information. Furthermore, the external ratings about those companies are usuall not available. According to Gama and Geraldes (2012), the rating process is very important for banks, who have to find a way to discriminate between the SMEs in terms of their creditworthiness. A failure to estimate creditworthiness of an SME correctly, will lead to an inefficient distribution of resources. In response, banks need credit risk models that are designed especially for SMEs. These are the main reasons why I decided to concentrate my empirical research on SMEs companies.

The definition for SMEs, according to European Commission (2014), is based on two elements, a number of employees and balance sheet size/yearly sales. A company is classified as SME if it has 10 to 250 employees and 2 million to 50 million yearly sales or 2 million to 43 million balance sheet size. Since I was limited with the number of companies in bankruptcy at the Slovenian market at the time of the research, I set the sample criteria to companies with yearly sales from 1 million to 15 million, according to last profit and loss account available. That was last year prior bankruptcy for defaulted companies and from the year 2013, for non-defaulted companies. I shrink the definition of SME to obtain more homogeneous groups and to exclude the influence of the company's size from the analysis. Volk (2012) stated that the size of a company is found as one of the most important ingredient of credit risk model by many authors, because smaller companies tend to be less diversified, have lower net worth and have more troubles with access to funding. Grunert et al. (2005) also restricted the observed population to medium sized companies' turnover between 25 and 250 million EUR on a minimum loan size 1.5 million. Their sample was taken at the German market, so the SMEs definition is different comparing it to the Slovenian market, due to the big market size differences.

5.1.2.2 Sample size

The number of companies included in the sample was another criteria. The decision was partially influenced by the size of the Slovenian market and partially other author's work.

Aragon (2004) worked with a sample of 52 companies, from which 22 belonged to the group of default, Mileris (2010) used financial data about 100 Lithuanian companies (50 – defaulted, 50 – not defaulted), Altman (1968) chose a sample of 66 corporations, 33 in each group and Lugovskaya (2009) composed the estimation sample of 520 companies (260 defaulted and 260 non-defaulted). My sample consists of 80 companies, divided into two equal groups (40 default, 40 no-default), which is also a practice for other authors. My sample is larger than Aragon's

and Altman's, slightly smaller than Mileris's and also smaller than the one used by Lugovskava. However, I was very limited with the size of the Slovenian market, which is, compared to the Russian market that Lugovskava analyzed, very small, so the sample also reflects the market's size. My main limitation was that at the time of the analysis, only around 45 companies that went bankrupt in the last three years and with the size characteristics described before, were in bankruptcy, according to the databases GVIN and AJPES, so I analyzed almost the whole population in the chosen segment.

5.1.2.3 Definition of default

Broad definition of default is "failure to meet financial obligations". Aragon (2004) defined the default as a company with over 90-day delay in payments. According to Crouhy et al. (2001), default events are the one that follow, when the major failure of payment obligations occurs. This is why they classified default events as bankruptcy or restructuring. Bankruptcy usually marks the end of a company in its present form. It is a final point of a process and the moment when it is clearly recognized that the company cannot pay its obligations. This is one reason why I took the definition of default as "company in bankruptcy" in my empirical research. Another one is that the data about companies with over 90-day delay in payments were not publicly available, while data about the bankruptcy are. Furthermore, according to its definition, bankruptcy is "unconditional state of default".

5.1.2.4 Sampling method

For forming a sample and collecting data, I used a database GVIN, (Companies in Slovenian market, n.d.) where the randomly prepared list of all companies in Slovenia filtered by different criteria is available. From that list, I could randomly choose companies for my sample. For choosing companies in default, I applied the criteria "in bankruptcy" (*Slovenian: v stečaju*) and I got the list of companies also filtered by their yearly sales, that are currently in bankruptcy.

5.1.3 Indicators used in the analysis

In the following chapter, I will describe indicators that were used in the analysis. Comparing to Altman (1968) that applied six financial ratios (working capital to total assets, retained earnings to total assets, earnings before interest and taxes to total assets, market value equity to book value of the total debt and sales to total assets), I applied eight financial indicators. I also gathered and commented information on four non-financial indicators and included two of them in the analysis, due to the descriptive variables limitations (explained later on). Grunert et al. (2005) that explore the role of non-financial indicators in internal credit ratings, similar to my analysis, also took two non-financial data, management quality and borrowers position at the market. When I was selecting ratios, I relied on the existing studies that I have already described in the chapters before, as well as on findings gathered in the interview. An overview of financial and non-financial indicators that appear in the studies is presented in the Tables 3 and Table 4. Indicators that were frequently cited by different authors are marked with label "high" (they

seem to be of high importance), the ones that were sometimes cited by different authors, but not appear that often, were labelled with “medium” and the ones that were only mentioned in a few author’s work, are marked with “low”. I also marked with x, which of them were mentioned in the interview as the most important, when analyzing credit risk in a bank.

Table 3. Overview of financial indicators*

Financial indicator	**Literature**	**Mentioned in the interview**
EBIT/interest expense	Medium	
Current ratio	High	x
Liability (debt)/equity	High	x
Cash flow or EBITDA/ net debt or total debt	High	x
Pretax return on capital or ROE	High	
LTD/capital	Low	
Total debt/capitalization	Low	
ROA	Medium	
Loans to assets ratio	Low	
Equity to assets ratio	High	x
Operating return (EBITDA) on assets	Medium	
Operating margin or operating profit/sales	Medium	
Debt structure or senior debt to subordinated debt	Low	
CAPEX	Low	x
Inventories turnover	Low	x
Accounts payable turnover	Medium	x
Accounts receivable turnover	Medium	x
Accounts receivable to accounts payable	Low	x
Net cash cycle	Low	
Variable cost to fixed cost	Low	
Short term cash and investment over total assets	Low	
Equity or price to book value	Low	
Operating cash flow/ revenues	Low	
Assets turnover (sales/total assets)	Medium	

Note. *High – appear in almost all studies
Medium – appear in majority of studies
Low – appear only in some studies.

Table 4. Overview of non-financial* indicators

Non - financial indicator	**Literature**	**Mentioned in the interview**
Industry within company is operating	High	x
Competition within the industry	High	x
Market share and size	High	x
Diversification of products and services	Medium	
Growth potential	Medium	
Technology	Low	
Quality of products and services	Low	
Management quality	High	
Barriers to entry	Medium	
Company age	High	x
number of days a company has blocked bank account per year	Low	x
Environmental assessment	Low	
Importance of the quality of the information provided	Medium	
Country risk	Medium	
Third-party support	Medium	x
Risk associated with longer-term facilities	Low	
Presence of security	Medium	x
CEO duality	Low	
Owner concentration/ organizational structure	Low	x
Reduced number of outside directors on the board	Low	
Number of bank-borrower relationships	Low	x
Delays in repayments of other bank loans	Low	x
Negative news in the media	N/A	x
Identifying the successor	N/A	x
Future strategy	N/A	x

Note. *High – appear in almost all studies
Medium – appear in majority of studies
Low – appear only in some studies
N/A – was not found in many studies, but was mentioned in the interview.

It can be seen from the tables above that some of the financial indicators measure similar things. We could divide them in a few groups that measure different aspects of companies business, for example operating profitability, financial profitability, financial structure, operating efficiency and liquidity. I tried to choose ratios that will represent different aspects, so the entire risk of company's operations could be covered. On the other hand, there were more limitations regarding non-financial indicators, because some of them are difficult to quantify (for example management quality) or are very time consuming to observe and difficult to gather (for example

borrower's future strategy). However, based on the tables above and some research limitations, the following financial and non-financial indicators were chosen.

5.1.3.1 Financial indicators

- Current ratio

Current ratio measures company's liquidity, by comparing current assets with current liabilities (current assets divided by current liabilities). Higher current ratio indicates that the current liabilities are more likely going to be paid. So the higher the current ratio, the greater short term creditor protection. A surplus of current assets over current liabilities is a protector against losses that may occur in selling inventory, collecting accounts receivable or liquidating current investment. When analyzing company's current ratio, one must examine the quality of the current assets and the type of the current liabilities (Siegl & Shim, 2000). Considering the quality of the inputs was also one of the focus points in the interview with a risk manager and it is also one of the limitations of ratings that the risk manager highlighted. According to Lemke (1970), current ratio has been indicated as one of the prime criteria of liquidity by risk managers already in the 70's. He pointed out that several empirical studies in the USA, at that time, reported the current ratio as a focus point in assessing creditworthiness of a borrower, and an assured minimum ratio has sometimes been mandatory. That paradigm has changed in the last decades. In the interview, I have already discussed that this rule was neglected in banks in the past years and many companies have problems nowadays because of that.

- Company's leverage (Equity /Total assets)

One of the measures of the company's leverage is equity divided by total assets. It shows the amount of protection available to creditors with exclusion of a company's size (when compare it to total assets) - the percentage of equity in the balance sheet of the company. A low ratio means that company have quite risky business, because if the loss occurs, a company will run out of equity (Siegl & Shim, 2000). However, the ratio could also indicate the type of business. For example, banks usually have low equity to total assets, but their assets are liquid. Conversely, this ratio also shows the percentage of debt in the balance sheet of the company if one apply 1 - equity ratio.

Ratio indicates the company's capital structure and financial leverage. This ratio could also be negative, since the amount of equity in the balance sheet can be negative. Negative ratio is an indicator that a company has problems, so thus it can act as a warning signal for banks.

- Operating income/ sales

Operating income or EBIT represents the surplus of operating revenues over operating expenses and indicates how well a company is doing its core business. From operating income, income statements that do not relate to core business activities are excluded. Such activites are, for example, extraordinary gains or losses. The ratio also excludes financial expenses and revenues, such as interest expense and dividend income (Siegl & Shim, 2000). To compare different sized companies, I divided operating income by the amount of sales and got the so-called operating margin. This measure indicates operating profitability and is an indirect measure of company's efficiency. Company's core business is more profitable if the operating income is higher. Ratio

could also be negative, due to the fact that operating income could be negative. Negative ratio acts the same as negative equity to assets ratio, as a warning signal for banks.

- EBITDA/ net debt

EBITDA/ net debt represents the percentage of the company's EBITDA in the company's net debt. It is the measure of how quickly the company can repay its debt. EBITDA is an acronym that means: company's Earnings Before the deduction of Interest, Tax, Depreciation and Amortization expenses. By eliminating these items, one could easier make the comparison of different companies' states. This ratio is also helpful for evaluating companies with different capital structures, tax rates and depreciation policies. EBITDA also give banks information on how much money a company could generate before making payments to creditors and the taxes (EBITDA, n.d.). The difference between operating income mentioned before (EBIT) and EBITDA is that in EBITDA amortization and depreciation is also included. Difference between amortization and depreciation is that amortization spread an intangible asset's cost over that asset's useful life, while depreciation do the same with the tangible asset's cost. Net debt is calculated as a sum of all debt in the company's balance sheet (short and long term), minus money that a company has in their balance sheet. The EBITDA/ Net debt ratio is useful to compare different sized companies, to know how much debt they have relative to their EBITDA.

- ROA (return on assets)

Return on assets is ratio that compares net income or pretax profit with total assets. It is used to measure how much is earned on each dollar of assets invested. It is an indicator of management efficiency, because it measures how efficient is company' management at using its assets to generate earnings (Siegl & Shim, 2000). In my analysis, I took income before taxes to exclude the effect of taxes.

- ROE (return on equity)

Return on equity is ratio that compares net income or pretax profit with total equity. It is used to measure profitability of shareholder's investment. It is a modification of the DUPONT formula, which equals total assets (investment turnover), times the profit margin, times the equity multiplier (Siegl & Shim, 2000). However, according to Bragg (2007), ROE could also be increased by obtaining new debt and using it to buy back shares. That could be easily done by company's management to improve the ratio to be more favorable. So one has to combine this ratio with the amount of debt, or equity ratio that I have already mentioned before.

In a group of observed companies in default there were, in many cases, both components of ROE, pretax profit and total equity, negative. As a consequence, ROE was positive, which did not make sense, since the profit was negative. This is why I decided to use one of the values in the ROE formula in absolute number and got a negative return, when both the profit and the equity was negative.

- Accounts receivable turnover

Accounts receivable, as measure of operating efficiency, compares company's sales with the average accounts receivables. Average accounts receivable are calculated in a way, to sum

accounts receivable in balance sheet with accounts receivable from previous year and divide them by two, to get the average of those numbers. This ratio measures the realization risk in account receivable. It also shows how well is company collecting debts. The lower the ratio, the longer receivables are not being paid and the less likely they're being collected. Also, there is an opportunity cost of crediting company's clients (Siegl & Shim, 2000). One of the main findings from the interview with the risk manager was that one has to analyze also the quality of accounts receivable and the strategy that companies have with the due ones. Those facts are usually not included in the ratings, since a rating model only takes the amount of receivables.

- Accounts payable turnover

Accounts payable turnover measures short term liquidity and assess the rate, at which a company pays off suppliers. This ratio divides total supplier's purchases (total costs of material) with average accounts payable. Average accounts payable are calculated to sum accounts payable in balance sheet, with accounts payable from previous year and divide them by two, to get the average of those numbers. The ratio represents the number of times per year that purchases are being paid off. For example, turnover of 12 times per year is the equivalent of 30 accounts payable days (Bragg, 2007). Accounts payable are usually compared through the time. An increasing ratio through time shows more frequent payment of accounts payable and vice versa. Accounts payable can also be compared with different competitors and the industry average.

5.1.3.2 Non-financial indicators

- Number of years at the market

In my analysis, a number of years at the market were set as a number of years from a company's establishment, until the year of the analysis (2014). This information can be seen in the register of companies in Slovenia. Volk (2012) in his work found that younger companies default more often, because they are more sensitive to shocks. His sample has 65,557 observations of non-default and 2,887 observations of default, when I used the sample which was size limited (as mentioned in chapter Sample definition and criteria). The ratio was only significant at $P = 0.024$, when all data was analyzed, however after eliminating outliers ratio was not significant anymore ($P = 0.079$). Thus, any conclusions on a ratio cannot be made.

- Number of days of blocked bank accounts per year

Another non-financial indicator that could separate companies into default and non-default is also a variable, which measures a number of days a company has blocked a bank account per year. This information is available at the Slovenian database GVIN, where one can see blockades at all bank accounts that a company has in the last three years. There is also information about the exact number of days and dates of blocked accounts. For non-defaulted companies, I limited the period of observation to last year and for companies in the default, I limited the period to one year prior bankruptcy. Information about the date of the bankruptcy is publicly available at AJPES (AJPES, n.d.). Volk (2012) with given sample showed that defaulted companies' bank accounts were on average blocked 106 days per year, whereas accounts for companies with no default were on average blocked only 6 days per year. In my

sample, defaulted companies' bank accounts were on average blocked 93 days per year, whereas accounts for companies with no default were on average blocked 13 days per year. This variable is significant with P = 0.000.

- Type of the industry

As already mentioned in the chapter about non-financial indicators in the literature, an industry is crucial for financial health of a company. The type of industry cannot be directly included in the discriminant function. Variable could only be included with dummy variables, what is difficult with many industries (many dummies). However, I wanted to know if companies in default were active in similar industries as healthy companies or if some industries appeared to be represented more in one of the groups. I used standard classification of activities, which is the obligatory national standard used for recording, collecting, processing, analyzing, mediating and disseminating data connected with the activity. It is used for defining the main activity and for classifying business subjects and their units for the needs of official and other administrative data collections (Standard classification of activities, 2008). In the Table 1 in Appendix A I stated standard classification of activities of activities based on wider classification, where each company is listed in one of the 21 industries.

Volk (2012) in his sample found that defaulters and non-defaulters are equivalently distributed across sectors, with the highest representativeness of Commerce (28%), Manufacturing (18%), Professional activities (17%) and Construction (11%). Sectors like electricity, gas and water supply, information and communication, professional activities and public services are less risky than manufacturing, whereas only accommodation and food service has on average a higher statistically significant default probability. I found that if comparing both groups, there is a higher variety of different industries among active companies in the market (companies were randomly taken). In sample of 40 active companies at the market, there were 13 industries represented, while in sample of 40 companies in bankruptcy, there were only 8 industries represented. From the Table 5 we can see that companies in bankruptcy mostly worked in the industry C – manufacturing (42.5%), while in group of healthy companies, manufacturing is also most represented. However, "only" 22.5% of non-defaulted companies are working in industry C – manufacturing, comparing it to the 42.5% of defaulting companies. Representativeness of companies working in the industry F – construction is also quite different among groups. Among companies in default, 20% of companies were present in construction, while among non-default companies that percent is only 0.05. We could conclude that operating in an industry, construction is more risky. That makes sense, since the recent financial crises really had a large effect on the construction industry in Slovenia.

Table 5. Percentage of companies in different industries*

Industry	Default in %	Non-default in %
C	42.5	22.5
G	20.0	20.0
F	20.0	0.05
M	0.05	12.5
I	-	12.5
L	0.025	0.05
H	0.05	-
Q	-	0.05
B	-	0.05
S	0.025	-
R	0.025	-
K		0.025
N	-	0.025
D	-	0.025
A	-	0.025
E		0.025

* Classification of industries is presented in Appendix A

- Competition within the industry

As I have mentioned before, many authors expressed competition in the industry and the company's market share as crucial for driving a company's health. Importance is not solely on the industry, but also on the company's position within the industry. I quantify the competition in the industry with a number of subjects present in narrow term of the industry's classification. I used the definition of the industry based on standard classification of activities specified with a letter and five numbers (A.01.240 – growing of pome fruits and stone fruits). For each company analyzed, that information is possible to find in database GVIN.

From the Table 6, we could conclude that the number of the subject in the industry does not have a major influence on estimation of company's default. We can see that there were more than half (52.5%) of companies in default in the industries with more than 500 competitors, while in the group of healthy companies, there were a bit less than half (45%) of such cases. 30% of companies in default were presented in the industries with more than 1000 competitors, while in the group of healthy companies, there were 25% of such cases. When assessing credit risk, the market share of the competitors is more important, than their number. However, in rating models, there is difficult to assess market share of different competitors, especially for SME companies, where publicly available data are more limited as at large, publicly traded companies. This is another limitation of rating models. Loan officers who are usually responsible for collecting non-financial indicators have difficulties in estimating competition at

the market, thus many times such data cannot be reliable. We can see that a number of subjects in the industry is not such a good predictor of competition in the segment.

Table 6. Percentage of companies that operate in industry with a certain number of competitors

Number of competitors	**Default in %**	**Non – default in %**
1-50	12.5	12.5
50-100	12.5	12.5
100-300	17.5	15.0
300-500	5.0	15.0
500-700	22.5	17.5
700-1000	-	2.5
1000-3000	5.0	10.0
3000-5000	22.5	10.0
5000-10000	2.5	5.0

5.2 Results

I made six different discriminant functions in SPSS, as described before. Through the percentage of original cases correctly classified and canonical correlation, I compared the accuracy of predictions from all functions. In the Table 7 below, one can see the percent of correct classification of units. In this table it is shown that inclusion of non-financial indicators contribute to a better classification result (a number of cases correctly classified increased, when adding non-financial indicators). Furthermore, Table 7 also show the percent of variability that is explained with financial and non-financial variables. This percent explained with financial and non-financial variables is much higher than the percent of variability, explained with only financial variables.

Table 7. Classification results and canonical correlations from discriminant function analysis

	Financial indicators			**Financial and non-financial indicators**		
	Version	Classification results in %	Canonical correlation in %	Version	Classification results in %	Canonical correlation in %
All data	A	76.3	30.03	D	80.0	46.37
Replacing outliers with means	B	80.0	45.42	E	86.3	67.9
Elimination of outliers	C	81.7	45.42	F	93.3	67.9

Firstly, I will briefly comment on results in the Table 7 when only financial indicators were observed. The percent of original cases correctly classified in the first function that included all data is 76.3. We can see that outliers elimination contribute to a better result, since the difference of original group cases correctly classified between version A, with all data and version B, where outliers are eliminated, is 3.7 percentage points. There is also a difference between replacing outliers by mean value and eliminating them. The difference of original group cases correctly classified between the two methods in cases B and C, is 1.7 percentage point. In term of relative numbers, version A model classified 19 cases wrong, in version B model classified 16 cases wrong and in version C, where instead of 80 units, there were only 60 units included, 11 of them were not correctly classified. Canonical correlation of discriminant function shows the percent of variability that is explained with ratios included in analysis. In version with all data, 30.03% of variability is explained with financial ratios. After the outliers' elimination, the variability explained increased for 15.39 percentage points.

Versions D, E and F include additional two non-financial components. From the Table 7 one can see that adding those components in case of all observations, it reflects in 3.7 percentage point increase in correct classification of original group cases, comparing to version A that did not include non-financial indicators. When eliminating outliers and replacing their values with mean value, 86.3% of original group cases were correctly classified, which represents 6.3 percentage point increase, comparing it to a version with only financial indicators. If we change the method used and not replace the missing values with mean value, but compute from the group size, 93.3% of original group cases were correctly classified, which reflects in 11.6 percentage point increase comparing to version C, without non-financial indicators. In version F, in group of non-default, all cases were correctly classified and in group of default, only three cases were not correctly classified. However in this version, I only have 19 observations in group of default and 26 in group of non-default, comparing to version C, where there were 27 companies in group of default and 33 in group of non-default. Furthermore, the inclusion of

non-financial indicators increased the variability explained for 16.34 percentage points, in case after outliers' elimination is increased for 22.48 percentage points.

In the next two chapters, I will more precisely comment the results of discriminant functions that contain financial indicators and the results of discriminant functions that contain also non-financial indicators. I will comment on different parameters and significance of variables as well.

5.2.1 Results with financial indicators

From the Table 8 for version A (version with all data), we can see that 76.3% of original cases were correctly classified, which means that the function is accurate in 76,3% of predictions. In group of non-default, this percent of correct predictions was 75 and in group of default 77.5.

Table 8. Classification results in version A

		Default or non-default	**Predicted Group Membership**		**Total**
			Non-default	Default	
Original	Count	Non-default	30	10	40
		Default	9	31	40
	%	Non-default	75	25	100
		Default	22.5	77.5	100

From the Table 9 the test of group's equality means that we can see that in this version, at the confidence level 5% (P = 0.05), three ratios are not statistically significant. Those ratios are EBITDA/Net debt, ROE and accounts receivable turnover. From the Appendix D we can see that EBITDA/ Net debt and ROE are ratios that have the highest relative standard deviation in the group of defaulted companies, compared with other ratios. That is going to be solved with the elimination of outliers in the next versions. Accounts receivable turnover has a standard deviation that is especially high in the group of non-default companies.

Table 9. Test of equality of group mean values in version A

Indicator	**Wilks' Lambda**	**F**	**Df1**	**Df2**	**Significance**
Current ratio	0.931	5.820	1	78	0.018
Equity/assets	0.816	17.610	1	78	0.000
Operating income/sales	0.932	5.647	1	78	0.020
EBITDA/NET DEBT	0.991	0.693	1	78	0.408
ROA	0.877	10.986	1	78	0.001
ROE	0.997	0.225	1	78	0.636
Accounts receivable turnover	0.965	2.833	1	78	0.096
Accounts payable turnover	0.891	9.579	1	78	0.003

Canonical correlation of discriminant function is 0.548, which means that 30.03% of variability is explained with ratios included in analysis. Structure matrix (Appendix D) shows the correlations of each variable with discriminant function. The highest correlations have equity to total assets, ROA and accounts payable. Those ratios are best predictors in the first function.

From the correlation matrix (Appendix D), we can see that variables mostly have weak correlations (under 0.310). However, equity on total assets ratio and ROA are very strongly correlated (0.861), while accounts receivable turnover and accounts payable turnover are strongly correlated (0.512). This may indicate the violation of multicollinearity assumption mentioned before in chapter about discriminant analysis. Indicators equity on total assets and ROA are in some aspects similar, especially because they have the same denominator – total assets and because the retain profit (numerator in ROA ratio) is part of the equity in balance sheet (numerator in equity to total assets ratio). Although those indicators tend to be similar, they have important differences already presented in the chapter that describe indicators included in the analysis. To diagnose multicollinearity, one could calculate variance-inflating factor (VIF). If this factor is greater than 10, there is a sign of multicollinearity (Gjurati, 2003). The calculation for correlation between equity on total assets ratio and ROA show that VIF is 7.2, which is smaller than 10. However, outliers could have great impact on correlations, so in the next versions outliers were eliminated. Next versions that will be described in the following text, show that the correlation between equity on total assets ratio and ROA decrease, so there is even less sign of multicollinearity.

In the second version (version B), outliers were eliminated and 20 values at different variables were replaced by group means. In group of default, 13 units at different variables were replaced and in group of non-default, 7 units at different variables were replaced. This leads to better classifications results as in the first version. From the Table 10 below it could be seen that 80.0% of original cases were correctly classified, more specific in group of non-default, this percent of correct predictions was 85 and in group of default 75.

Table 10. Classification results in version B

		Default or non default	**Predicted Group Membership**		**Total**
			Non default	Default	
Original	Count	Non default	34	6	40
		Default	10	30	40
	%	Non default	85	15	100
		Default	25	75	100

From the Table 11 we can see that all ratios are after eliminating outliers more significant than before, EBITDA/NET DEBT and ROE became significant even now. The significance of accounts receivable turnover improved (P = 0.096), however it is still not under the confidence level 5% (P = 0.05).

Table 11. Test of equality of group mean values in version B

Indicator	Wilks' Lambda	F	Df1	Df2	Significance
Current ratio	0.840	11.080	1	58	0.002
Equity/assets	0.755	18.810	1	58	0.000
Operating income/ sales	0.841	10.992	1	58	0.002
EBITDA/NET DEBT	0.885	7.541	1	58	0.008
ROA	0.791	15.288	1	58	0.000
ROE	0.785	15.844	1	58	0.000
Accounts receivable turnover	0.947	3.231	1	58	0.077
Accounts payable turnover	0.856	9.777	1	58	0.003

Canonical correlation of discriminant function is 0.674, which means that 45.42% of variability is explained with ratios included in analysis. That is 15.4 percentage points better than the version A. Structure matrix (Appendix E) shows that the highest correlation with discriminant function has, same as in version A, equity to total assets, while all other correlations are also positive and closer than in the first version.

From correlation matrix (Appendix E), we can see that correlation between equity to total assets ratio and ROA is strong (0.658), however is not very strong as it was in previous version (0.861). Furthermore, account receivable turnover and accounts payable turnover have very weak correlation (0.054) now (before it was 0.512). On the other hand, correlations between operating income to sales and ROA (0.420) and operating income to sales and EBITDA/ Net debt (0.406) are higher than before, although they are still moderate. It is interesting that accounts receivable turnover is negatively correlated with current ratio (-0.215), while accounts payable turnover is positively correlated with the same ratio (0.202). With eliminating outliers the assumption of multicolinearity is even less violated as before, since the highest correlation between variables decreased from very strong (0.861) to strong (0.658). The accuracy of predictions also increased and the significance of the variables improved.

From the Table 12 below (last version with only financial data), it could be seen that in version C, 81.7% of original cases were correctly classified, more specific, in group of non-default this percent of accurate predictions was 87.9 and in group of default 74.1. This method of computing from the group size rather than replacing units by mean value contribute to more accurate prediction. Once again, as in version B, with eliminating outliers the percentage of original cases correctly classified only improved in group of non-default. Since only the method was changed comparing it to version B, ratios mean values and their significances are the same as in version B.

Table 12. Classification results in version C

		Default or non default	Predicted Group Membership		Total
			Non default	Default	
Original	Count	Non default	29	4	33
		Default	7	20	27
	%	Non default	87.9	12.1	100
		Default	25.9	74.1	100

To sum up the differences between different versions with financial ratios, I will compare some statistics between both groups in the following table. Statistics for verisons B and C (elimination of outliers) are the same, so I divided table below to versions with all data and version with elimination of outliers.

Table 13. Comparison in mean values and standard deviation between both groups for different versions

		Version with all data		Version with elimination of outliers	
Default or non-default		Mean	Std. Deviation	Mean	Std. Deviation
Non-default	Current ratio	1.3341	1.25800	1.2148	0.87963
	Equity/assets	0.2873	0.25394	0.2928	0.23652
	Operating income/sales	-0.0345	0.35871	0.0011	0.18805
	EBITDA/NET DEBT	0.1630	0.34293	0.1259	0.21874
	ROA	-0.0168	0.10156	-0.0052	0.07738
	ROE	0.1473	1.26128	-0.0187	0.54429
	Receivable	25.5634	71.15064	10.6020	13.90643
	Payable	6.9225	9.93123	5.0452	5.67026
Default	Current ratio	0.7532	0.85812	0.6068	0.39103
	Equity/assets	-0.1378	0.58816	-0.0493	0.37047
	Operating income/sales	-0.2126	0.30971	-0.2038	0.28806
	EBITDA/NET DEBT	1.9665	13.69919	-0.0700	0.33126
	ROA	0.3626	0.65197	-0.2874	0.40640
	ROE	1.8425	22.54262	-2.0507	2.87555
	Receivable	6.5442	6.64328	5.6301	3.92762
	Payable	2.0349	1.06128	1.5970	0.84663

From the Table 13 above, for both versions (all data and data after outliers elimination), I can conclude that defaulted companies have on average a lower current ratio. Their current ratio is

on average below one, while non-defaulted companies have current ratio on average above 1. Current ratio is a measure of liquidity, so as expected, a company with greater liquidity / higher current ratio, has a lower default probability. Defaulted companies have on average a negative equity/assets ratio, while healthy companies have on average a positive equity/total assets ratio. This negative sign indicates that companies with a lower equity amount default more often.

In version A, defaulted and non-defaulted companies have both on average a negative operating income to total sales ratio, however when we eliminate only two outliers, defaulted companies still have on average a negative operating income to total assets ratio, while healthy companies have on average a slightly positive operating income to total assets ratio. Operating income to sales is an indirect measure of efficiency, so as expected, more efficient companies with a higher ratio default less often.

With eliminating only two outliers, standard deviation of EBITDA/ net debt in the group of defaulted companies decreased from 13.7 to 0.33. Since the ratio is statistically significant only in version B or C, I will discuss results from this second version. Defaulted companies have on average a negative EBITDA/Net debt ratio, while non-defaulted have a positive EBITDA/Net debt ratio. This is due to the fact that defaulted companies have on average a negative EBITDA. We can conclude that companies with a negative EBITDA/Net debt default more often.

Defaulted companies have on average a lower ROA and ROE, however the average ROA and ROE are also slightly negative in the group of active companies at the market. Those two ratios are indicators of how efficient is the management at using its assets or equity to generate earnings. If the management is less efficient (lower ROA and ROE ratios), the possibility of default is higher.

Accounts receivable tend to be very different among companies in different industries, so they especially have a high standard deviation in the group of active companies at the market. Because this ratio is not statistically significant at confidence level 5%, we cannot make conclusions with a desired probability. For accounts payable turnover we can conclude that defaulted companies have on average a lower accounts payable turnover.

5.2.2 Results with financial and non-financial indicators

In the next three versions, non-financial indicators were included (a number of days that a company has blocked bank accounts and a number of years that a company is present at the market). It could be seen from the Table 14 that 80.0% of original cases were correctly classified, specifically in group of non-default, this percent of correct predictions was 85 and in group of default 75. The accuracy of predictions has comparing to version A (both versions contain all data) increased.

Table 14. Classification results in version D

		Default or non default	Predicted Group Membership		Total
			Non default	Default	
Original	Count	Non default	34	6	40
		default	10	30	40
	%	Don default	85	15	100
		Default	25	75	100

Since all other ratios have the same mean values and statistical significance as in version A, I only included two additional indicators in the Table 15 below. From this table we can see that in this version with all observations included, at the confidence level 5% (P = 0.05), both ratios are statistically significant. Especially variable a number of days of blocked accounts is highly significant.

Table 15. Test of equality of group mean values in version D

Indicator	Wilks' Lambda	F	Df1	Df2	Significance
Number of days blocked bank accounts	0.798	19.708	1	78	0.000
Number of years at the market	0.937	5.273	1	78	0.024

From correlation matrix (Appendix G), we can see that a number of days of blocked bank accounts has low correlation with other ratios, which means that this variable can highly contribute to explaining the function's variability. A number of years at the market is correlated with equity to total assets, however the correlation is moderate (0.398). Canonical correlation of discriminant function is 0.681, which means that 46.37% of variability is explained with ratios included in analysis, which is 16 percentage point higher than without inclusion of those additional indicators. The percent of variability explained is also higher than when having only financial data and eliminating outliers.

The highest correlation with a function has a new indicator that is included, a number of days of blocked bank accounts. We can conclude that this indicator is very important when estimating company's default. A number of days that a company has blocked bank accounts is also the variable that is inversely correlated with the function, while other indicators are positively correlated with the function. This is because higher values of that variable reflect in a lower possibility of default.

In next two versions, the units were eliminated same as in versions B and C before. It could be seen from the Table 16 below that in version E 86.3% of original cases were correctly classified, specifically in group of non-default, this percent of correct predictions was 90 and in group of

default 82.5. Comparing to version A and B, where only the percentage of original cases correctly classified in group of non-default improved with eliminating outliers, this percentage improved in both groups, regarding version E.

Table 16. Classification results in version E

		Default or non default	**Predicted Group Membership**		
			Non default	Default	Total
Original	Count	Non default	36	4	40
		default	7	33	40
	%	Non default	90	10	100
		default	17.5	82.5	100

Since additional outliers were eliminated at versions E and F (15 outliers), statistical significance of financial ratios has slightly changed. Due to the fact that those changes are very small, I will only comment on the significance of non-financial indicators in the Table 17 below. We can see that variable a number of days of blocked bank accounts is still statistically significant, while a number of years at the market is not significant anymore at confidence level 5% (however it is close with significance P = 0,079). We can conclude that the difference in mean values at that variable was partially driven by outliers.

Table 17: Test of equality of group mean values for version E

Indicator	**Wilks' Lambda**	**F**	**Df1**	**Df2**	**Significance**
Current ratio	0.827	8.984	1	43	0.005
Equity/ assets	0.678	20.456	1	43	0.000
Operating income/ sales	0.898	4.871	1	43	0.033
EBITDA/net debt	0.883	5.709	1	43	0.021
ROA	0.789	11.490	1	43	0.002
ROE	0.744	14.762	1	43	0.000
Accounts receivable turnover	0.963	1.644	1	43	0.207
Accounts payable turnover	0.844	7.953	1	43	0.007
Number of days blocked bank accounts	0.760	13.562	1	43	0.001
Number of years in the market	0.930	3.233	1	43	0.079

From correlation matrix (Appendix H), we can see that a number of days of blocked accounts is negatively correlated with current ratio (-0.284), but the correlation is weak. A number of years at the market is moderately correlated with EBITDA/ net debt (0.483). Canonical correlation of discriminant function is 0.824, which means that 67.9% of variability is explained with ratios included in analysis, which is 21.5 percentage point higher than the version with all data. We can see that with eliminating outliers, we highly contribute to a better explanation of variability.

The highest correlation in structure matrix (Appendix H) has indicators equity to total assets, ROE and a number of days of blocked bank accounts. A number of days of blocked bank accounts is negatively correlated with function, which means that higher the number of block bank accounts, higher the default estimation, when at all other indicators, higher ratio reflects at lower default estimation.

It could be seen from the Table 18 that in version F 93.3% of original cases were correctly classified, specifically in group of non-default, all cases were correctly classified, while in group of default, this percent was 84.2. In all cases, except in version A, the predicted group membership was more accurate in group of non-default. This method, where values are not replaced with mean values, contributes to a better result. Statistical significance of variables is the same as in version E (Table 19), so the method does not have an influence on the statistical significance.

Table 18. Classification results in version F

		Default or non default	**Predicted Group Membership**		**Total**
			Non default	Default	
Original	Count	Non default	26	0	26
		Default	3	16	19
	%	Non default	100	0	100
		Default	15.8	84.2	100

Table 19. Test of equality of group mean values for version F

Indicator	Wilks' Lambda	F	Df1	Df2	Significance
Current ratio	0.827	8.984	1	43	0.005
Equity/ assets	0.678	20.456	1	43	0.000
Operating income/ sales	0.898	4.871	1	43	0.033
EBITDA/net debt	0.883	5.709	1	43	0.021
ROA	0.789	11.490	1	43	0.002
ROE	0.744	14.762	1	43	0.000
Accounts receivable turnover	0.963	1.644	1	43	0.207
Accounts payable turnover	0.844	7.953	1	43	0.007
Number of days blocked bank accounts	0.760	13.562	1	43	0.001
Number of years in the market	0.930	3.233	1	43	0.079

To sum up, the differences between different versions with all data and versions with elimination of outliers, I will compare mean value and standard deviation between both groups in the following table.

Table 20. Comparison in mean values and standard deviation between both groups for different versions with additional non-financial indicators

		Version with all data		**Version with elimination of outliers**	
Default or non-default		Mean	Std. Deviation	Mean	Std. Deviation
Non-default	Current ratio	1.3341	1.25800	1.2359	0.84983
	Equity/assets	0.2873	0.25394	0.3181	0.25142
	Operating income/sales	-0.0345	0.35871	0.0025	0.20537
	EBITDA/net debt	0.1630	0.34293	0.1420	0.23981
	ROA	-0.0168	0.10156	-0.0017	0.08217
	ROE	0.1473	1.26128	0.0321	0.57558
	Receivable	25.5634	71.15064	9.6294	11.98693
	Payable	6.9225	9.93123	5.6288	6.20519
	Blocked accounts	12.5750	36.20872	7.8462	22.95682
	Years	18.7250	8.14921	17.6154	6.84150
Default	Current ratio	0.7532	0.85812	0.6012	0.41555
	Equity/assets	0.1378	0.58816	-0.0951	0.36211
	Operarting income/sales	-0.2126	0.30971	-0.1500	0.25795
	EBITDA/net debt	1.9665	13.69919	-0.0753	0.37005
	ROA	-0.3626	0.65197	-0.2983	0.43764
	ROE	1.8425	22.54262	-2.4774	3.27537
	Receivable	6.5442	6.64328	5.9264	4.37544
	Payable	2.0349	1.06128	1.5729	0.87402
	Blocked accounts	92.6000	108.10508	69.5263	81.39026
	Years	23.4250	10.05851	21.2105	6.31206

In versions with eliminating outliers, financial ratios' mean values and standard deviations differ. This is the case because in versions E and F, additional outliers were eliminated (18 outliers), since their values at variables number of days blocked bank accounts and number of years, were outside ratios three standard deviations. However, the differences are not that big, for example mean value at current ratio of non-defaulted companies in version E and F is 1.2359 (standard deviation 0.84983), while in version B and C it is 1.2148 (standard deviation 0.87963). That is why I will only comment on two new indicators that are included, although I included all values in the table 20.

We can conclude from all versions that defaulted companies have on average a higher number of days of blocked bank accounts. The difference in both group mean values is quite big. With elimination of outliers, I reduced indicator's standard deviation at both groups. Variable number of years at the market is in version with all units significant at P = 0.024, but when eliminating outliers, it is not significant anymore at 5% confidence level but at 7.9% confidence level. The value is close to 5%, however because the indicator is not significant, I cannot make any conclusions.

6 FINDINGS AND FURTHER RESEARCH

6.1 Findings of the analysis

I conducted a discriminant function analysis to predict if a company would default or not. In the first set o functions, the predictor variables were financial ratios: current ratio, equity to total assets, operating income to sales, EBITDA to net debt, ROA, ROE, accounts receivable turnover and accounts payable turnover. In the second set of functions, predictor variables were all financial ratios mentioned before and two non-financial ratios: a number of days of blocked bank accounts per year and a number of years that a company is present at the market. After elimination of outliers, significant mean value differences were observed for all predictors, except account receivable turnover and a number of years at the market. Discriminant function, after the outliers were eliminated, in version with financial ratios explained 45.42% of between group variability, while the version with adding also non-financial indicators explained 67.9% of between group variability as shown in the Table 22. A closer analysis of the structure matrix in version with only financial indicators revealed 7 good predictors (higher than 0.3), namely equity to assets, ROE, ROA, current ratio, operating income to sales, accounts payable turnover and EBITDA to net debt, while account receivable turnover is a poor predictor. In version with all indicators (financial and non-financial), discriminant analysis revealed 5 good predictors (higher than 0,3), namely equity to assets, ROE, a number of blocked bank accounts, ROA and current ratio, while accounts payable turnover, EBITDA to net debt, operating income to sales, a number of years at the market and accounts receivable turnover are poor predictors. Classification results in Table 21 below showed that 80% of original cases, after replacing outliers with variables mean values, were correctly classified when only financial ratios were observed, while 86.3% of original cases were correctly classified when all indicators were included and outliers were replaced with variables mean values. This percent in table below, shows the accuracy of the discriminant function prediction. Thus, there is a 6.3 percentage point improvement in accuracy of a model if also non-financial indicators are included. The improvement in accuracy is even higher if outliers are completely eliminated, as it is shown in Table 21, however in this case, a number of units in population is smaller as well.

Table 21. Classification results

Version	Financial indicators in %	Financial and non-financial indicators in %
All data	76.3	80.0
Replacing outliers with variables means	80.0	86.3
Elimination of outliers	81.7	93.3

Table 22. Canonical correlation

Version	Financial indicators in %	Financial and non-financial indicators in %
All data	30.03	46.37
Replacing outliers with variables means	45.42	67.9
Elimination of outliers	45.42	67.9

At the beginning, I set the following hypothesis: A model that consists of a combination of financial and non-financial indicators, leads to a better prediction of company's default, than a model consisting of only financial indicators. Since there is a difference between classification results in discriminant function analysis presented in the Table 21, between the model that includes only financial indicators and the model that includes both, financial and non-financial indicators, the hypothesis cannot be rejected.

In general, discriminant function analysis showed that defaulted companies have on average lower current ratio, lower equity total assets ratio, lower operating income to sales ratio, lower EBITDA/ Net debt ratio, lower ROA and ROE, lower accounts payable turnover and higher number of days that a company has block bank accounts, comparing to non-defaulted companies. Among some others, a significantly useful non-financial indicator to separate companies into default and non-default is a variable, which measures a number of days a company has blocked bank accounts per year. It shows that in a given sample with all units, defaulted companies' bank accounts were on average blocked 93 days per year, whereas accounts for companies with no default were on average blocked only 19 days per year.

According to Uddin et al. (2013), discriminant analysis is very outlier sensitive. Hence outlier should be identified and excluded from the analysis. I dropped all the observations that lie outside three standard deviations, which improved the accuracy of the model. In version where only financial ratios were included, eliminating outliers improved the accuracy of the model for at least 3.7 percentage points (depends on the method taken) and in version where all indicators were included, the classification results improved for at least 6.3 percentage points (also depends on the method taken). As already mentioned, when removing outliers, the method for

outlier's substitution contribute to the final result as well. When using "compute from the group size", results are better than using "replace missing values with variable means".

From the SPSS printouts in Appendixes E,F,H and I we can see that some ratios divide between groups based on their sign. Those are equity to total assets and operating income to sales that have negative values in group of defaulted companies and positive in group of active companies.

We can also see from the data that variables were on average not correlated between each other, which means that each of them contribute to the explaining of the variability. Correlations also depend on different versions. Equity to total assets and ROA were most highly correlated in all versions and their correlation varies from 0.658 to 0.861. However, the level of multicollinearity is below the trashold (mentioned before) that indicates mullticolinearity problems.

Non-financial indicators' industry and competition in the market were not included directly into the analysis, because of the nature of the variables, however the data were also gathered and observed. A higher variety of different industries were present among active companies in the market. Defaulted companies mostly worked in the industry C – manufacturing (42.5%), while in group of healthy companies, 22.5% of companies are working in that industry. Defaulted companies also worked in the industry F – construction (20%), while among non-default companies that percent is 0.05. Although in literature, competition is an important indicator when predicting company's default in my sample, the number of the subjects in the industry does not have a major influence on predicting company's default. I can conclude that competition is not well defined with the variable number of the subject in the industry.

Although Saunders and Allen (2002) argued that company's age is a good proxy for its payment reputation and other authors found that younger companies default more often, in my sample, the variable "number of years at the market" was not statistically significant. This is probably the case, because I used the sample which was size limited, while other authors also included micro companies that included many companies at the establishment as well. The ratio was only significant when all data was analyzed, however after eliminating outliers ratio was not significant anymore (although the significance P = 0.079 is close to the trashold level of P = 0.05). Thus, any conclusions on a number of years at the market cannot be made.

Beside the contribution of non-financial indicators to the prediction of company's default, I also observed, which of the variables used are the best predictors. Structure matrix shows correlations of each variable with discriminant function and can explain, which ratios are good and which are poor predictors. In version with financial data, the best predictors were equity to total assets, ROA and accounts payable turnover. When we also include the additional two non-financial indicators, the best predictor was a number of days that a company had blocked accounts. After the elimination of outliers, the best predictors were equity to total assets, ROE and a number of blocked accounts, ROA and current ratio. I can conclude that the best predictors are in general equity to total assets and a number of days that a company had blocked accounts. Good predictors are also ROE, ROA, current ratio and accounts payable turnover.

Those findings could be applied in a way that indicators with better explanatory power would have higher weight when designing internal rating model.

6.2 Suggestions for the further research

When including also non-financial indicators into the model, the accuracy of predicting default of the company increased. However, it would be interesting to see how this could be applied to different samples and with different analysis. Further research could be done with other methods that I described, for example with logit and probit model. It would also be interesting to see, what are the results if different criteria for default is applied, for example delay in repayments of bank loans for more than 90 days. In order to set that kind of criteria, one has to gain access to information about that delays from banks. The database about the delays in banks is large, so the sample of companies included in the analysis would be bigger, which would result in more representative findings. Furthermore, that kind of research could also be applied to different sized companies, from SMEs that I've analyzed to large companies and micro companies. That will reflect in the analysis of what kind of default prediction model is suitable for different segments of a company. Finally, more inputs or ratios could be included in the analysis, especially in segment of non-financial indicators. However, those indicators usually cannot be gathered from public sources (especially for micro companies or SMEs). One option would be to gain information from banks, but because the information between a bank and a client is confidential, the second option would have to be chosen, which is, gathering information directly from companies. This can sometimes be very difficult, because companies are not willing to share this kind of information, despite the information would only be used for the purpose of a research.

CONCLUSION

Internal ratings are widely used in commercial banks. According to Treacy and Carey (2000), internal ratings are not only used for assessing attractiveness of customer relationship, but also for portfolio monitoring, loan loss reserve analysis, loan/business line pricing, profitability analysis, internal capital allocation and return on capital analysis. Furthermore, the Basel Committee put the rating systems in central position for evaluating capital requirements when introduced an IRB approach, which allows banks to use their own internal assessment of their counterparties and exposures.

Internal ratings in commercial banks consist of several indicators that serve as an input for rating models. When designing a rating model, banks need to decide, which attributes have to be taken into account and what weight needs to be applied for each of them. When I was selecting ratios for my analysis, I was relaying on the existing studies, as well as on primary information gathered in the interview with the risk manager.

For my research, I chose a sample that includes SME companies in the Slovenian market. To achieve growth, SMEs usually need external funding, because the equity market for small companies is not very well developed. According to Gama and Geraldes (2012), there is also lack of publicly available information and external ratings regarding SME, so banks need to asses creditworthiness of SME companies through the rating process very carefully. Because of the need to develop accurate rating models for SMEs, I decided to include that kind of companies to my sample. I included companies from the Slovenian market, because there is a lack of research, regarding inclusion of different indicators in internal ratings in the Slovenian market. To answer the research question, I applied discriminant function analysis, because it is simple, but still explains a great deal of variability, it reduces analyst's space of dimensionality and covers a great deal of information with a small number of measurements, due to variables correlation.

Adding non-financial indicators in the discriminant function analysis, it reflects in 3.7 percentage point increase in the correct classification of original group cases and in 16.34 percentage point increase in variability explained. When eliminating outliers and replacing them with mean values, 6.3 percentage points increase in correct classification and 22.48 percentage point increase in variability explained can be seen if including non-financial indicators. If eliminating outliers from the sample and compute from the group size, there is 11.6 percentage point increase in classification results and 22.48 percentage point increase in variability explained, between version with only financial data and the version with a combination of financial and non-financial indicators.

I set the following hypothesis at the beginning: A model that consists of a combination of financial and non-financial indicators, leads to a better prediction of company's default, than a model consisting of only financial indicators. Since there is a difference between classification results in discriminant function analysis, between the model that includes only financial indicators and the model that includes both, financial and non-financial indicators, the hypothesis cannot be rejected.

Despite the importance and the usage of internal ratings in banks, rating is still not the core information, on which a decision is based. In loan approval decisions, ratings are used more like a tool for decision making or additional information about the borrower. This is the case, because in rating models, there are not all important indicators included, otherwise the models would be too complicated. On the other hand, risk managers have to consider all information available. The main limitation of ratings that could be seen in banks is that a model only takes a number, while the content is usually more important.

Further research could be done with other models that I described, for example with logit and probit model. It would also be interesting to see the results if different criteria for default would be applied. Different criteria would also increase the number of units included in the sample. Furthermore, that kind of research could also be applied to different sized companies, from

SMEs that I've analyzed, to large companies and micro companies. Finally, more inputs or ratios could be included into the analysis, especially in a segment of non-financial indicators.

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APPENDIXES

TABLE OF APPENDIXES

Appendix A: Standard classification of activities

Table 1. Standard classification of activities

Code	Name
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage, waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

Source: *Standardna klasifikacija dejavnosti 2008* [Standard classification of activities 2008], 2014.

Appendix B: Data for companies in default

Table 2. Data for companies in default

	1	2	3	4	5	6	7	8	9	10	11	12	13
current ratio	0,65	0,16	0,91	0,41	0,17	1,11	0,13	0,36	0,50	0,57	0,15	0,18	0,09
equity/total assets	0,16	-3,01	-0,11	-0,03	0,02	0,28	-1,17	-0,37	-0,84	-0,15	-0,72	-0,32	0,16
operating income/sales	-1,08	-0,50	-0,41	-0,01	0,46	-0,13	-0,11	0,01	-0,23	-0,07	-0,74	-0,83	-0,20
NET DEBT/EBITDA	-13,74	-0,27	-0,72	4,37	12,11	-2,93	-16,57	5,29	-0,97	-0,79	-12,16	13,68	16,50
pretax profit/assets	-0,18	-3,71	-0,31	-0,05	0,01	-0,20	-1,43	-0,03	-0,85	-0,05	-0,32	-1,04	-0,55
pretax profit/equity	-1,10	1,23	2,71	1,54	0,37	-0,73	1,22	0,08	1,01	0,32	0,45	3,25	-3,41
acc. receivable turnover	5,76	17,71	3,01	7,13	14,21	1,19	13,28	13,02	6,28	8,91	7,86	4,19	6,81
acc.payable turnover	2,27	1,60	1,58	2,29	0,19	2,32	3,05	1,31	4,07	4,08	0,16	1,50	1,07
blocked accounts (nmb of days)	83	53	29	21	104	16	0	243	0	8	365	14	182
industry	C	F	C	C	L	F	G	C	C	G	C	G	R
competition	50	3108	515	572	534	1745	3013	623	26	73	45	3013	16
number of years on the market	23	8	9	24	17	23	17	23	2	23	10	36	24

table continues

continued

	14	15	16	17	18	19	20	21	22	23	24	25	26
current ratio	0,26	0,66	1,10	0,18	0,40	0,29	0,82	1,29	0,97	0,26	1,05	1,05	0,46
equity/total assets	-0,74	-0,05	0,12	-0,02	-0,29	0,07	0,17	-0,01	0,15	-0,79	0,00	0,41	0,17
operating income/sales	-0,18	-0,20	0,03	-0,34	-0,14	0,21	-0,01	0,00	0,00	-0,82	-0,14	0,07	-0,43
NET DEBT/EBITDA	-36,04	-2099,72	0,01	-6,35	-22,33	1,12	17,69	-75,55	37,95	-35,31	-2,10	3,53	-10,81
pretax profit/assets	-1,38	-0,33	-0,03	-0,21	-0,29	-0,13	-0,02	-0,03	-0,05	-0,55	-0,58	0,00	-0,41
pretax profit/equity	1,86	6,58	-0,22	13,06	1,00	-1,90	-0,10	2,12	-0,36	0,70	-140,04	0,00	-2,38
acc. receivable turnover	8,59	2,73	2,57	3,99	3,24	39,45	6,87	4,10	4,92	1,25	8,30	8,96	2,46
acc.payable turnover	2,64	2,69	1,29	1,80	3,72	3,21	2,70	0,20	3,23	3,47	2,67	2,31	1,65
blocked accounts (nmb of days)	48	26	70	102	71	171	61	0	50	332	34	365	284
industry	G	C	C	G	G	C	F	M	G	H	C	H	C
competition	3013	88	572	576	374	657	3108	4361	155	86	203	5790	69
number of years on the market	15	24	38	10	23	22	40	15	22	14	38	7	40

table continues

continued

	27	28	29	30	31	32	33	34	35	36	37	38	39	40
current ratio	1,35	0,60	0,97	5,50	0,87	0,61	1,11	0,28	1,26	0,88	0,46	0,84	1,04	0,19
equity/total assets	0,24	-0,11	0,41	0,17	0,05	-0,02	0,02	0,13	0,13	0,15	0,30	0,25	0,09	-0,42
operating income/sales	0,00	-0,25	-0,11	-0,04	-0,16	-0,27	-0,16	-0,34	-0,10	0,07	-0,45	0,05	-0,16	-0,84
NET DEBT/EBITDA	9,39	-14,57	-1,85	49,86	-28,88	-11,05	-9,62	-26,51	-17,61	8,55	-8,11	2,21	33,73	-2,65
pretax profit/assets	-0,03	-0,05	-0,14	-0,01	-0,07	-0,13	-0,09	-0,13	-0,12	0,00	-0,09	0,02	-0,20	-0,74
pretax profit/equity	-0,12	0,50	-0,34	-0,06	-1,47	6,20	-4,67	-0,95	-0,89	-0,01	-0,31	0,08	-2,18	1,77
acc. receivable turnover	3,61	2,20	2,28	4,08	4,80	1,06	1,40	11,67	10,16	5,44	1,99	7,19	4,03	1,96
acc.payable turnover	2,97	0,75	1,34	2,22	1,11	0,76	1,26	0,98	3,25	1,18	2,47	1,37	3,21	1,46
blocked accounts (nmb of days)	9	0	0	25	50	236	29	33	101	67	246	0	0	176
industry	C	F	F	C	F	F	M	C	C	C	G	C	S	F
competition	107	245	3108	572	3108	1745	4361	412	203	623	290	20	220	36
number of years on the market	25	37	38	24	40	22	23	23	23	25	40	25	23	22

Appendix C: Data for non-defaulted companies

Table 3. Data for non-defaulted companies

	1	2	3	4	5	6	7	8	9	10	11	12	13
current ratio	0,11	0,79	0,82	0,13	0,47	0,20	6,32	0,26	1,82	0,44	0,52	0,83	1,01
equity/total assets	0,19	-0,06	0,32	0,09	0,37	0,16	0,85	0,24	0,73	0,19	0,09	0,30	0,69
operating income/sales	0,25	-0,09	0,08	0,15	0,05	-0,27	0,03	0,07	0,06	0,06	-0,20	0,03	0,07
NET DEBT/EBITDA	11,06	0,00	16,89	15,00	8,76	15,40	0,00	5,27	0,00	7,13	-11,37	2,87	2,48
pretax profit/assets	0,00	-0,41	0,00	0,00	-0,01	0,07	0,02	0,00	0,06	0,01	-0,07	0,01	0,02
pretax profit/equity	0,01	7,22	0,01	-0,01	-0,01	0,45	0,02	0,00	0,08	0,05	-0,80	0,04	0,03
acc. receivable turnover	21,82	388,67	4,13	7,16	20,87	7,31	3,14	9,01	5,11	8,64	5,81	6,15	24,19
acc.payable turnover	43,27	43,67	0,44	0,44	3,83	2,98	4,40	2,18	4,14	26,71	1,39	5,65	4,19
blocked accounts (nmb of days)	0	0	0	0	0	16	0	7	0	0	0	0	0
industry	L	G	M	L	I	I	C	B	F	D	C	A	I
competition	534	683	9795	1245	507	2483	50	55	245	1246	857	58	507
number of years on the market	15	14	19	7	24	10	24	40	23	10	25	19	24

table continues

continued

	14	15	16	17	18	19	20	21	22	23	24	25	26
current ratio	1,44	0,64	0,21	1,10	0,91	3,40	2,69	0,77	1,12	2,85	1,05	0,31	1,03
equity/total assets	0,44	-0,16	0,55	0,05	0,04	0,44	0,69	0,21	0,41	0,72	0,05	0,20	0,12
operating income/sales	0,08	-0,05	0,01	0,10	0,09	0,05	0,03	0,23	-0,02	0,06	0,00	0,00	-0,92
NET DEBT/EBITDA	2,76	0,00	5,75	16,42	10,37	0,00	1,10	4,95	6,74	0,00	0,00	5,64	-2,28
pretax profit/assets	0,04	-0,25	0,00	0,00	0,00	0,06	0,02	0,04	-0,03	0,09	0,00	0,00	-0,28
pretax profit/equity	0,09	1,57	0,00	0,00	0,00	0,13	0,03	0,20	-0,08	0,13	0,10	-0,01	-2,34
acc. receivable turnover	3,93	15,91	66,10	59,52	10,52	3,88	1,77	249,15	2,43	21,87	5,27	1,61	1,64
acc.payable turnover	3,06	5,17	4,59	2,09	0,23	7,25	4,43	5,78	7,75	23,83	4,81	2,15	7,82
blocked accounts (nmb of days)	0	20	82	146	0	0	0	0	0	0	0	86	0
industry	M	Q	I	G	N	C	B	M	G	C	F	G	C
competition	4361	476	143	339	384	555	55	9795	320	657	208	3013	25
number of years on the market	23	9	24	22	11	25	23	6	18	13	4	21	3

table continues

continued

	27	28	29	30	31	32	33	34	35	36	37	38	39	40
current ratio	3,43	1,04	1,12	1,39	4,13	2,35	1,08	0,54	1,58	0,97	1,70	1,61	1,12	0,04
equity/total assets	0,01	0,33	0,44	0,39	0,39	0,03	0,07	0,17	0,69	0,34	0,45	0,24	0,19	-0,20
operating income/sales	0,02	0,03	0,04	0,16	0,07	0,18	0,05	-0,13	-0,02	0,11	0,03	0,03	0,05	-1,95
NET DEBT/EBITDA	75,70	6,30	0,54	5,16	5,73	0,00	7,11	815,79	0,00	0,00	1,83	5,15	8,51	39,15
pretax profit/assets	0,00	0,01	0,02	0,04	0,05	0,00	-0,01	-0,12	0,02	0,05	0,04	0,03	0,02	-0,22
pretax profit/equity	0,11	0,03	0,04	0,10	0,13	0,00	-0,11	-0,71	0,02	0,16	0,09	0,14	0,12	1,11
acc. receivable turnover	1,53	2,34	6,07	7,97	3,61	6,95	13,75	5,18	8,61	4,09	7,71	2,86	2,61	0,21
acc.payable turnover	3,36	1,75	2,82	9,67	5,06	4,37	3,35	2,14	5,55	3,63	3,61	2,15	1,81	5,41
blocked accounts (nmb of days)	0	146	0	0	0	0	0	0	0	0	0	0	0	0
industry	C	C	M	Q	G	E	C	I	G	C	M	G	G	K
competition	20	147	4361	108	374	79	90	2483	576	35	4361	46	372	159
number of years on the market	18	4	23	21	12	24	25	36	22	24	25	18	21	20

Appendix D: SPSS output for version A

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		80	100,0
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	0	,0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	0	,0
Total		80	100,0

Group Statistics

default or non-default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
non-default	current ratio	1,3341	1,25800	40	40,000
	equity/assets	,2873	,25394	40	40,000
	operating income/sales	-,0345	,35871	40	40,000
	EBITDA/NET DEBT	,1630	,34293	40	40,000
	ROA	-,0168	,10156	40	40,000
	ROE	,1473	1,26128	40	40,000
	accounts_receivable	25,5634	71,15064	40	40,000
	accounts_payable	6,9225	9,93123	40	40,000
default	current ratio	,7532	,85812	40	40,000
	equity/assets	-,1378	,58816	40	40,000
	operating income/sales	-,2126	,30971	40	40,000
	EBITDA/NET DEBT	1,9665	13,69919	40	40,000
	ROA	-,3626	,65197	40	40,000
	ROE	1,8425	22,54262	40	40,000
	accounts_receivable	6,5442	6,64328	40	40,000
	accounts_payable	2,0349	1,06128	40	40,000
Total	current ratio	1,0437	1,10915	80	80,000
	equity/assets	,0747	,49835	80	80,000
	operating income/sales	-,1235	,34482	80	80,000
	EBITDA/NET DEBT	1,0648	9,67097	80	80,000
	ROA	-,1897	,49518	80	80,000
	ROE	,9949	15,88652	80	80,000
	accounts_receivable	16,0538	51,11292	80	80,000
	accounts_payable	4,4787	7,43601	80	80,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current ratio	,931	5,820	1	78	,018
equity/assets	,816	17,610	1	78	,000
operating income/sales	,932	5,647	1	78	,020
EBITDA/NET DEBT	,991	,693	1	78	,408
ROA	,877	10,986	1	78	,001
ROE	,997	,225	1	78	,636
accounts_receivable	,965	2,833	1	78	,096
accounts_payable	,891	9,579	1	78	,003

Pooled Within-Groups Matrices[a]

	current ratio	equity/assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable
Covariance								
current ratio	1,159	,151	,074	,409	,093	,711	-6,674	-,450
equity/assets	,151	,205	,044	,447	,182	,229	-2,344	-,115
OI/sales	,074	,044	,112	,306	,044	,253	1,283	,103
EBITDA/NET DEBT	,409	,447	,306	93,893	,548	-2,791	-5,143	-1,046
ROA	,093	,182	,044	,548	,218	-,374	-2,225	-,196
ROE	,711	,229	,253	-2,791	-,374	254,880	39,323	4,716
accounts_receivable	-6,674	-2,344	1,283	-5,143	-2,225	39,323	2553,273	182,879
accounts_payable	-,450	-,115	,103	-1,046	-,196	4,716	182,879	49,878
Correlation								
current ratio	,039	,184	,041	-,123	,184	,041	-,123	-,059
equity/assets	,310	1,000	,288	,102	,861	,032	-,102	-,036
operating income/sales	,205	,288	1,000	,094	,279	,047	,076	,044
EBITDA/NET DEBT	,039	,102	,094	1,000	,121	-,018	-,011	-,015
ROA	,184	,861	,279	,121	1,000	-,050	-,094	-,059
ROE	,041	,032	,047	-,018	-,050	1,000	,049	,042
accounts_receivable	-,123	-,102	,076	-,011	-,094	,049	1,000	,512
accounts_payable	-,059	-,036	,044	-,015	-,059	,042	,512	1,000

Log Determinants

default or non-default	Rank	Log Determinant
non-default	8	-,718
default	8	8,297
Pooled within-groups	8	14,705

Test Results

Box's M		851,383
F	Approx.	21,064
	df1	36
	df2	20471,770
	Sig.	,000

Summary of Canonical Discriminant Functions

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,430[a]	100,0	100,0	,548

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,699	26,480	8	,001

Standardized Canonical Discriminant Function Coefficients

	Function
	1
current ratio	,226
equity/assets	,754
operating income/sales	,174
EBITDA/NET DEBT	-,227
ROA	-,106
ROE	-,160
accounts_receivable	,120
accounts_payable	,502

Structure Matrix

	Function
	1
equity/assets	,724
ROA	,572
accounts_payable	,534
current ratio	,416
operating income/sales	,410
accounts_receivable	,291
EBITDA/NET DEBT	-,144
ROE	-,082

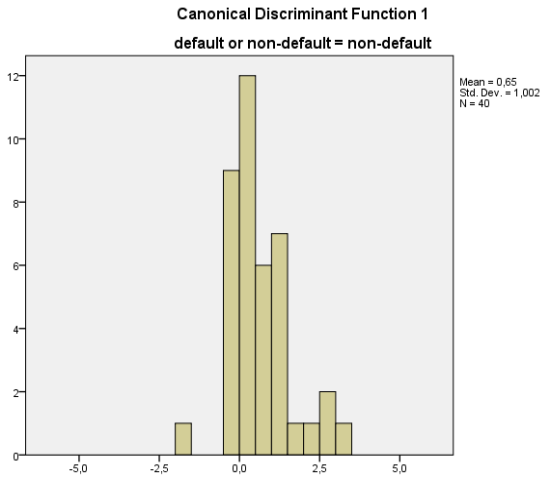
Functions at Group Centroids

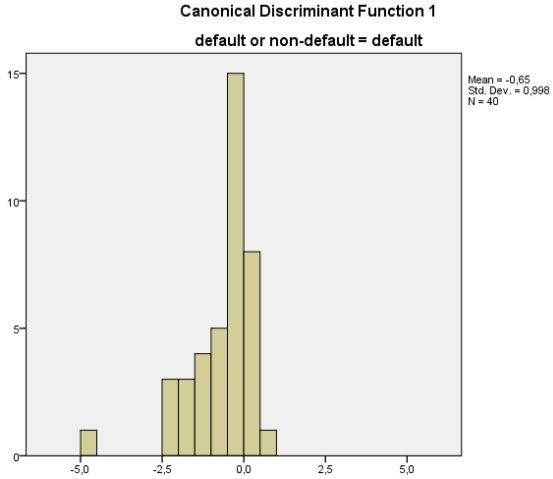
	Function
default or non-default	1
non-default	,648
default	-,648

Classification Function Coefficients

	default or non-default	
	non-default	default
current ratio	1,051	,778
equity/assets	4,463	2,306
operating income/sales	-1,406	-2,079
EBITDA/NET DEBT	,004	,035
ROA	-3,836	-3,540
ROE	-,014	-,001
accounts_receivable	,005	,002
accounts_payable	,129	,036
(Constant)	-2,603	-1,768

Separate-Groups Graphs





Classification Results[a,c]

			Predicted Group Membership		
		default or non-default	non-default	default	Total
Original	Count	non-default	30	10	40
		default	9	31	40
	%	non-default	75,0	25,0	100,0
		default	22,5	77,5	100,0
Cross-validated[b]	Count	non-default	27	13	40
		default	12	28	40
	%	non-default	67,5	32,5	100,0
		default	30,0	70,0	100,0

a. 76,3% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 68,8% of cross-validated grouped cases correctly classified.

Appendix E: SPSS output for version B

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		60	75,0
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	20	25,0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	20	25,0
Total		80	100,0

Group Statistics

default_non_default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
non default	current ratio	1,2148	,87963	33	33,000
	equity_to_assets	,2928	,23652	33	33,000
	operating_income_to_sales	,0011	,18805	33	33,000
	EBITDA_to_net_debt	,1259	,21874	33	33,000
	ROA	-,0052	,07738	33	33,000
	ROE	-,0187	,54429	33	33,000
	accounts_receivable_turnover	10,6020	13,90643	33	33,000
	accounts_payable_turnover	5,0452	5,67026	33	33,000
default	current ratio	,6068	,39103	27	27,000
	equity_to_assets	-,0493	,37047	27	27,000
	operating_income_to_sales	-,2038	,28806	27	27,000
	EBITDA_to_net_debt	-,0700	,33126	27	27,000
	ROA	-,2874	,40640	27	27,000
	ROE	-2,0507	2,87555	27	27,000
	accounts_receivable_turnover	5,6301	3,92762	27	27,000
	accounts_payable_turnover	1,5970	,84663	27	27,000
Total	current ratio	,9412	,76164	60	60,000
	equity_to_assets	,1389	,34681	60	60,000
	operating_income_to_sales	-,0911	,25751	60	60,000
	EBITDA_to_net_debt	,0377	,28978	60	60,000
	ROA	-,1322	,30995	60	60,000
	ROE	-,9331	2,20087	60	60,000
	accounts_receivable_turnover	8,3646	10,85856	60	60,000
	accounts_payable_turnover	3,4935	4,55487	60	60,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current ratio	,840	11,080	1	58	,002
equity_to_assets	,755	18,810	1	58	,000
operating_income_to_sales	,841	10,992	1	58	,002
EBITDA_to_net_debt	,885	7,541	1	58	,008
ROA	,791	15,288	1	58	,000
ROE	,785	15,844	1	58	,000
accounts_receivable_turnover	,947	3,231	1	58	,077
accounts_payable_turnover	,856	9,777	1	58	,003

Pooled Within-Groups Matrices[a]

	current ratio	equity/assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable
Covariance								
current ratio	,495	,071	,034	,007	,049	,117	-1,612	,604
equity/assets	,071	,092	,020	,016	,056	,028	-,091	,177
OI/sales	,034	,020	,057	,027	,028	,138	,430	-,008
EBITDA/NET DEBT	,007	,016	,027	,076	,012	,091	,245	-,049
ROA	,049	,056	,028	,012	,077	,072	-,101	-,028
ROE	,117	,028	,138	,091	,072	3,870	2,254	-,026
accounts_receivable	-1,612	-,091	,430	,245	-,101	2,254	113,612	2,426
accounts_payable	,604	,177	-,008	-,049	-,028	-,026	2,426	18,060
Correlation								
current ratio	1,000	,332	,202	,037	,249	,085	-,215	,202
equity/assets	,332	1,000	,275	,186	,658	,047	-,028	,137
operating income/sales	,202	,275	1,000	,406	,420	,295	,169	-,008
EBITDA/NET DEBT	,037	,186	,406	1,000	,154	,168	,083	-,042
ROA	,249	,658	,420	,154	1,000	,132	-,034	-,023
ROE	,085	,047	,295	,168	,132	1,000	,107	-,003
accounts_receivable	-,215	-,028	,169	,083	-,034	,107	1,000	,054
accounts_payable	,202	,137	-,008	-,042	-,023	-,003	,054	1,000

Log Determinants

default_non_default	Rank	Log Determinant
non default	8	-9,583
default	8	-9,483
Pooled within-groups	8	-3,510

Test Results

Box's M		349,626
F	Approx.	8,253
	df1	36
	df2	10393,474
	Sig.	,000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,832[a]	100,0	100,0	,674

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,546	32,701	8	,000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
current ratio	,264
equity_to_assets	,273
operating_income_to_sales	-,017
EBITDA_to_net_debt	,223
ROA	,248
ROE	,447
accounts_receivable_turnover	,248
accounts_payable_turnover	,362

Structure Matrix

	Function
	1
equity_to_assets	,624
ROE	,573
ROA	,563
current ratio	,479
operating_income_to_sales	,477
accounts_payable_turnover	,450
EBITDA_to_net_debt	,395
accounts_receivable_turnover	,259

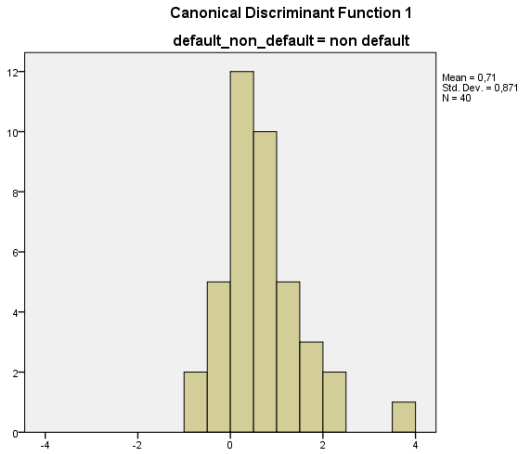
Functions at Group Centroids

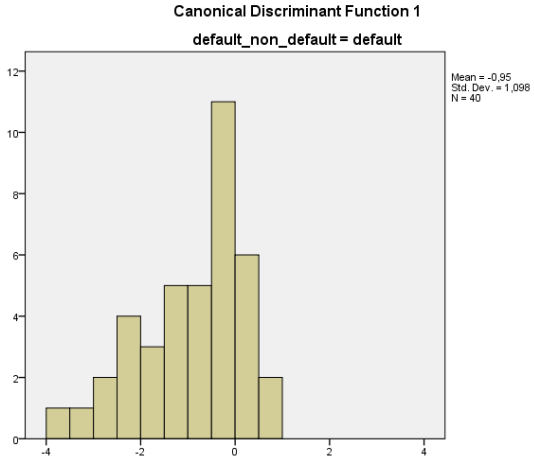
	Function
default_non_default	1
non default	,811
Default	-,992

Classification Function Coefficients

	default_non_default	
	non default	default
current ratio	2,791	2,114
equity_to_assets	2,951	1,330
operating_income_to_sales	-3,107	-2,978
EBITDA_to_net_debt	2,064	,603
ROA	-2,842	-4,449
ROE	-,075	-,484
accounts_receivable_turnover	,139	,097
accounts_payable_turnover	,138	-,015
(Constant)	-4,040	-2,979

Separate-Groups Graphs





Classification Results[a,c]

			Predicted Group Membership		
		default_non_default	non default	default	Total
Original	Count	non default	34	6	40
		default	10	30	40
	%	non default	85,0	15,0	100,0
		default	25,0	75,0	100,0
Cross-validated[b]	Count	non default	33	7	40
		default	14	26	40
	%	non default	82,5	17,5	100,0
		default	35,0	65,0	100,0

a. 80,0% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 73,8% of cross-validated grouped cases correctly classified.

Appendix F: SPSS output for version C

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		60	75,0
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	20	25,0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	20	25,0
Total		80	100,0

Group Statistics

default_non_default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
non default	current ratio	1,2148	,87963	33	33,000
	equity_to_assets	,2928	,23652	33	33,000
	operating_income_to_sales	,0011	,18805	33	33,000
	EBITDA_to_net_debt	,1259	,21874	33	33,000
	ROA	-,0052	,07738	33	33,000
	ROE	-,0187	,54429	33	33,000
	accounts_receivable_turnover	10,6020	13,90643	33	33,000
	accounts_payable_turnover	5,0452	5,67026	33	33,000
default	current ratio	,6068	,39103	27	27,000
	equity_to_assets	-,0493	,37047	27	27,000
	operating_income_to_sales	-,2038	,28806	27	27,000
	EBITDA_to_net_debt	-,0700	,33126	27	27,000
	ROA	-,2874	,40640	27	27,000
	ROE	-2,0507	2,87555	27	27,000
	accounts_receivable_turnover	5,6301	3,92762	27	27,000
	accounts_payable_turnover	1,5970	,84663	27	27,000
Total	current ratio	,9412	,76164	60	60,000
	equity_to_assets	,1389	,34681	60	60,000
	operating_income_to_sales	-,0911	,25751	60	60,000
	EBITDA_to_net_debt	,0377	,28978	60	60,000
	ROA	-,1322	,30995	60	60,000
	ROE	-,9331	2,20087	60	60,000
	accounts_receivable_turnover	8,3646	10,85856	60	60,000
	accounts_payable_turnover	3,4935	4,55487	60	60,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current ratio	,840	11,080	1	58	,002
equity_to_assets	,755	18,810	1	58	,000
operating_income_to_sales	,841	10,992	1	58	,002
EBITDA_to_net_debt	,885	7,541	1	58	,008
ROA	,791	15,288	1	58	,000
ROE	,785	15,844	1	58	,000
accounts_receivable_turnover	,947	3,231	1	58	,077
accounts_payable_turnover	,856	9,777	1	58	,003

Pooled Within-Groups Matrices[a]

	current ratio	equity/assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable
Covariance								
current ratio	,495	,071	,034	,007	,049	,117	-1,612	,604
equity/assets	,071	,092	,020	,016	,056	,028	-,091	,177
OI/sales	,034	,020	,057	,027	,028	,138	,430	-,008
EBITDA/NET DEBT	,007	,016	,027	,076	,012	,091	,245	-,049
ROA	,049	,056	,028	,012	,077	,072	-,101	-,028
ROE	,117	,028	,138	,091	,072	3,870	2,254	-,026
accounts_receivable	-1,612	-,091	,430	,245	-,101	2,254	113,612	2,426
accounts_payable	,604	,177	-,008	-,049	-,028	-,026	2,426	18,060
Correlation								
current ratio	1,000	,332	,202	,037	,249	,085	-,215	,202
equity/assets	,332	1,000	,275	,186	,658	,047	-,028	,137
operating income/sales	,202	,275	1,000	,406	,420	,295	,169	-,008
EBITDA/NET DEBT	,037	,186	,406	1,000	,154	,168	,083	-,042
ROA	,249	,658	,420	,154	1,000	,132	-,034	-,023
ROE	,085	,047	,295	,168	,132	1,000	,107	-,003
accounts_receivable	-,215	-,028	,169	,083	-,034	,107	1,000	,054
accounts_payable	,202	,137	-,008	-,042	-,023	-,003	,054	1,000

Log Determinants

default_non_default	Rank	Log Determinant
non default	8	-9,583
default	8	-9,483
Pooled within-groups	8	-3,510

Test Results

Box's M		349,626
F	Approx.	8,253
	df1	36
	df2	10393,474
	Sig.	,000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,832[a]	100,0	100,0	,674

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,546	32,701	8	,000

Standardized Canonical Discriminant

Function Coefficients

	Function
	1
current ratio	,264
equity_to_assets	,273
operating_income_to_sales	-,017
EBITDA_to_net_debt	,223
ROA	,248
ROE	,447
accounts_receivable_turnover	,248
accounts_payable_turnover	,362

Structure Matrix

	Function
	1
equity_to_assets	,624
ROE	,573
ROA	,563
current ratio	,479
operating_income_to_sales	,477
accounts_payable_turnover	,450
EBITDA_to_net_debt	,395
accounts_receivable_turnover	,259

Functions at Group Centroids

	Function
default_non_default	1
non default	,811
default	-,992

Classification Processing Summary

Processed		80
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	20
Used in Output		60

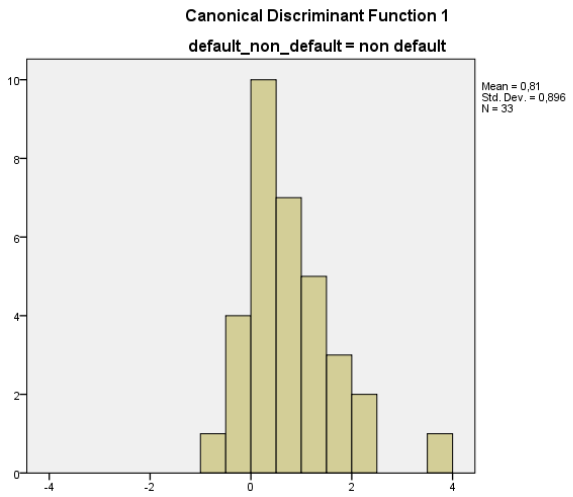
Prior Probabilities for Groups

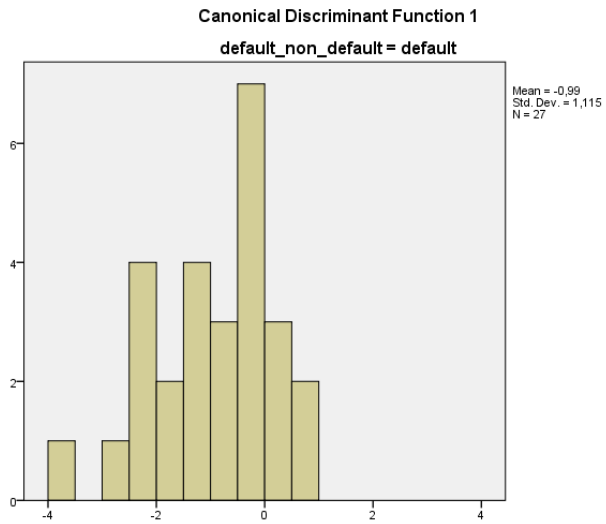
		Cases Used in Analysis	
default_non_default	Prior	Unweighted	Weighted
non default	,550	33	33,000
default	,450	27	27,000
Total	1,000	60	60,000

Classification Function Coefficients

	default_non_default	
	non default	default
current ratio	2,791	2,114
equity_to_assets	2,951	1,330
operating_income_to_sales	-3,107	-2,978
EBITDA_to_net_debt	2,064	,603
ROA	-2,842	-4,449
ROE	-,075	-,484
accounts_receivable_turnover	,139	,097
accounts_payable_turnover	,138	-,015
(Constant)	-3,945	-3,085

Separate-Groups Graphs





Classification Results[a,c]

		default_non_default	Predicted Group Membership		Total
			non default	default	
Original	Count	non default	29	4	33
		default	7	20	27
	%	non default	87,9	12,1	100,0
		default	25,9	74,1	100,0
Cross-validated[b]	Count	non default	29	4	33
		default	9	18	27
	%	non default	87,9	12,1	100,0
		default	33,3	66,7	100,0

a. 81,7% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 78,3% of cross-validated grouped cases correctly classified.

Appendix G: SPSS output for version D

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		80	100,0
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	0	,0
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	0	,0
Total		80	100,0

Group Statistics

default_non_default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Weighted
non default	current_ratio	1,3341	1,25800	40	40,000
	equity_to_assets	,2873	,25394	40	40,000
	operating_income_to_sales	-,0345	,35871	40	40,000
	EBITDA_to_net_debt	,1630	,34293	40	40,000
	ROA	-,0168	,10156	40	40,000
	ROE	,1473	1,26128	40	40,000
	accounts_receivable_turnover	25,5634	71,15064	40	40,000
	accounts_payable_turnover	6,9225	9,93123	40	40,000
	blocked_accounts	12,5750	36,20872	40	40,000
	n_years	18,7250	8,14921	40	40,000
default	current_ratio	,7532	,85812	40	40,000
	equity_to_assets	-,1378	,58816	40	40,000
	operating_income_to_sales	-,2126	,30971	40	40,000
	EBITDA_to_net_debt	1,9665	13,69919	40	40,000
	ROA	-,3626	,65197	40	40,000
	ROE	1,8425	22,54262	40	40,000
	accounts_receivable_turnover	6,5442	6,64328	40	40,000
	accounts_payable_turnover	2,0349	1,06128	40	40,000
	blocked_accounts	92,6000	108,10508	40	40,000
	n_years	23,4250	10,05851	40	40,000
Total	current_ratio	1,0437	1,10915	80	80,000
	equity_to_assets	,0747	,49835	80	80,000
	operating_income_to_sales	-,1235	,34482	80	80,000
	EBITDA_to_net_debt	1,0648	9,67097	80	80,000
	ROA	-,1897	,49518	80	80,000
	ROE	,9949	15,88652	80	80,000
	accounts_receivable_turnover	16,0538	51,11292	80	80,000
	accounts_payable_turnover	4,4787	7,43601	80	80,000
	blocked_accounts	52,5875	89,65429	80	80,000
	n_years	21,0750	9,39805	80	80,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current_ratio	,931	5,820	1	78	,018
equity_to_assets	,816	17,610	1	78	,000
operating_income_to_sales	,932	5,647	1	78	,020
EBITDA_to_net_debt	,991	,693	1	78	,408
ROA	,877	10,986	1	78	,001
ROE	,997	,225	1	78	,636
accounts_receivable_turnover	,965	2,833	1	78	,096
accounts_payable_turnover	,891	9,579	1	78	,003
blocked_accounts	,798	19,708	1	78	,000
n_years	,937	5,273	1	78	,024

Pooled Within-Groups Matrices[a]

	current_ratio	equity_to_assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable_	blocked_accounts	n_years
Covariance										
current_ratio	1,159	,151	,074	,409	,093	,711	-6,674	-,450	-14,607	,886
equity_to_assets	,151	,205	,044	,447	,182	,229	-2,344	-,115	-,475	1,648
OI/sales	,074	,044	,112	,306	,044	,253	1,283	,103	-4,183	,215
EBITDA/NET DEBT	,409	,447	,306	93,893	,548	-2,791	-5,143	-1,046	-18,094	17,488
ROA	,093	,182	,044	,548	,218	-,374	-2,225	-,196	2,745	1,099
ROE	,711	,229	,253	-2,791	-,374	254,880	39,323	4,716	-106,516	28,148
accounts_receivable_turnover	-6,674	-2,344	1,283	-5,143	-2,225	39,323	2553,273	182,879	50,746	-63,766
accounts_payable_turnover	-,450	-,115	,103	-1,046	-,196	4,716	182,879	49,878	-36,677	-9,802
blocked_accounts	-14,607	-,475	-4,183	-18,094	2,745	-106,516	50,746	-36,677	6498,889	-96,139
n_years	,886	1,648	,215	17,488	1,099	28,148	-63,766	-9,802	-96,139	83,792
Correlation										
current_ratio	1,000	,310	,205	,039	,184	,041	-,123	-,059	-,168	,090
equity_to_assets	,310	1,000	,288	,102	,861	,032	-,102	-,036	-,013	,398
OI/sales	,205	,288	1,000	,094	,279	,047	,076	,044	-,155	,070
EBITDA/NET DEBT	,039	,102	,094	1,000	,121	-,018	-,011	-,015	-,023	,197
ROA	,184	,861	,279	,121	1,000	-,050	-,094	-,059	,073	,257
ROE	,041	,032	,047	-,018	-,050	1,000	,049	,042	-,083	,193
accounts_receivable_	-,123	-,102	,076	-,011	-,094	,049	1,000	,512	,012	-,138
accounts_payable_	-,059	-,036	,044	-,015	-,059	,042	,512	1,000	-,064	-,152
blocked_accounts	-,168	-,013	-,155	-,023	,073	-,083	,012	-,064	1,000	-,130
n_years	,090	,398	,070	,197	,257	,193	-,138	-,152	-,130	1,000

Log Determinants

default_non_default	Rank	Log Determinant
non default	10	10,366
default	10	21,520
Pooled within-groups	10	27,496

Test Results

Box's M		901,112
F	Approx.	14,152
	df1	55
	df2	19647,125
	Sig.	,000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	,865[a]	100,0	100,0	,681

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,536	45,479	10	,000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
current_ratio	-,033
equity_to_assets	-,852
operating_income_to_sales	-,012
EBITDA_to_net_debt	,068
ROA	,114
ROE	,040
accounts_receivable_turnover	-,095
accounts_payable_turnover	-,225
blocked_accounts	,584
n_years	,601

Structure Matrix

	Function
	1
blocked_accounts	,541
equity_to_assets	-,511
ROA	-,404
accounts_payable_turnover	-,377
current_ratio	-,294
operating_income_to_sales	-,289
n_years	,280
accounts_receivable_turnover	-,205
EBITDA_to_net_debt	,101
ROE	,058

Functions at Group Centroids

	Function
default_non_default	1
non default	-,918
default	,918

Classification Processing Summary

Processed		80
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		80

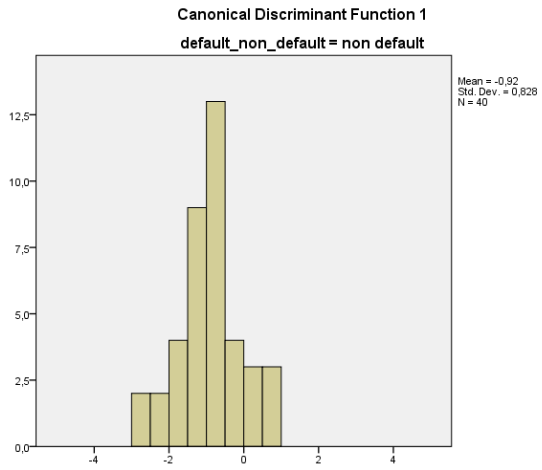
Prior Probabilities for Groups

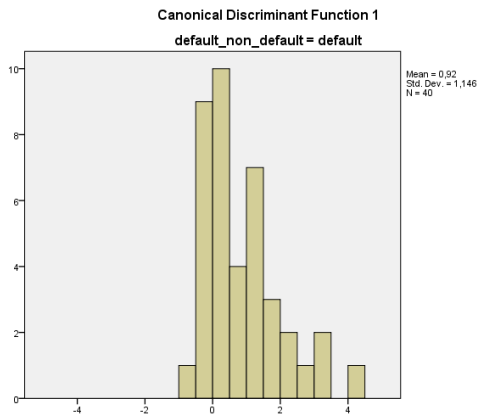
default_non_default	Prior	Cases Used in Analysis	
		Unweighted	Weighted
non default	,500	40	40,000
default	,500	40	40,000
Total	1,000	80	80,000

Classification Function Coefficients

	default_non_default	
	non default	default
current_ratio	1,354	1,298
equity_to_assets	,721	-2,735
operating_income_to_sales	-,765	-,828
EBITDA_to_net_debt	-,042	-,029
ROA	-2,415	-1,968
ROE	-,039	-,035
accounts_receivable_turnover	,007	,003
accounts_payable_turnover	,188	,129
blocked_accounts	,010	,023
n_years	,289	,410
(Constant)	-5,230	-7,776

Separate-Groups Graphs





Classification Results[a,c]

		default_non_default	Predicted Group Membership: non default	Predicted Group Membership: default	Total
Original	Count	non default	34	6	40
		default	10	30	40
	%	non default	85,0	15,0	100,0
		default	25,0	75,0	100,0
Cross-validated[b]	Count	non default	32	8	40
		default	13	27	40
	%	non default	80,0	20,0	100,0
		default	32,5	67,5	100,0

a. 80,0% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 73,8% of cross-validated grouped cases correctly classified.

Appendix H: SPSS output for version E

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		45	56,3
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	35	43,8
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	35	43,8
Total		80	100,0

Group Statistics

default_non_default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Weighted
non default	current ratio	1,2359	,84983	26	26,000
	equity_to_assets	,3181	,25142	26	26,000
	operating_income_to_sales	,0025	,20537	26	26,000
	EBITDA_to_net_debt	,1420	,23981	26	26,000
	ROA	-,0017	,08217	26	26,000
	ROE	,0321	,57558	26	26,000
	accounts_receivable_turnover	9,6294	11,98693	26	26,000
	accounts_payable_turnover	5,6288	6,20519	26	26,000
	n_blocked_accounts	7,8462	22,95682	26	26,000
	n_years	17,6154	6,84150	26	26,000
default	current ratio	,6012	,41555	19	19,000
	equity_to_assets	-,0951	,36211	19	19,000
	operating_income_to_sales	-,1500	,25795	19	19,000
	EBITDA_to_net_debt	-,0753	,37005	19	19,000
	ROA	-,2983	,43764	19	19,000
	ROE	-2,4774	3,27537	19	19,000
	accounts_receivable_turnover	5,9264	4,37544	19	19,000
	accounts_payable_turnover	1,5729	,87402	19	19,000
	n_blocked_accounts	69,5263	81,39026	19	19,000
	n_years	21,2105	6,31206	19	19,000
Total	current ratio	,9679	,76255	45	45,000
	equity_to_assets	,1436	,36354	45	45,000
	operating_income_to_sales	-,0619	,23871	45	45,000
	EBITDA_to_net_debt	,0502	,31697	45	45,000
	ROA	-,1269	,32272	45	45,000
	ROE	-1,0275	2,47956	45	45,000
	accounts_receivable_turnover	8,0659	9,63810	45	45,000
	accounts_payable_turnover	3,9163	5,12779	45	45,000
	n_blocked_accounts	33,8889	62,91741	45	45,000
	n_years	19,1333	6,79104	45	45,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current ratio	,827	8,984	1	43	,005
equity_to_assets	,678	20,456	1	43	,000
operating_income_to_sales	,898	4,871	1	43	,033
EBITDA_to_net_debt	,883	5,709	1	43	,021
ROA	,789	11,490	1	43	,002
ROE	,744	14,762	1	43	,000
accounts_receivable_turnover	,963	1,644	1	43	,207
accounts_payable_turnover	,844	7,953	1	43	,007
n_blocked_accounts	,760	13,562	1	43	,001
n_years	,930	3,233	1	43	,079

Pooled Within-Groups Matrices[a]

	current_ratio	equity_to_assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable_	blocked_accounts	n_years
Covariance current_ratio	,492	,062	,022	,012	,045	,087	-1,931	,480	-11,056	1,005
equity_to_assets	,062	,092	,013	,021	,061	-,025	,246	,130	-,825	,849
OI/sales	,022	,013	,052	,034	,023	,175	,384	-,046	-1,820	,451
EBITDA/NET DEBT	,012	,021	,034	,091	,016	,118	,295	-,100	,581	,964
ROA	,045	,061	,023	,016	,084	,029	-,177	-,068	,122	,527
ROE	,087	-,025	,175	,118	,029	4,683	2,897	-,227	-22,254	3,916
accounts_receivable_turnover	-1,931	,246	,384	,295	-,177	2,897	91,553	5,972	95,534	6,195
accounts_payable_turnover	,480	,130	-,046	-,100	-,068	-,227	5,972	22,706	-19,913	-6,299
blocked_accounts	-11,056	-,825	-1,820	,581	,122	-22,254	95,534	-19,913	3079,398	2,636
n_years	1,005	,849	,451	,964	,527	3,916	6,195	-6,299	2,636	43,891
Correlation current_ratio	1,000	,293	,137	,058	,222	,057	-,288	,144	-,284	,216
equity_to_assets	,293	1,000	,192	,232	,696	-,038	,085	,090	-,049	,423
OI/sales	,137	,192	1,000	,499	,339	,354	,175	-,042	-,143	,297
EBITDA/NET DEBT	,058	,232	,499	1,000	,187	,181	,102	-,070	,035	,483
ROA	,222	,696	,339	,187	1,000	,046	-,064	-,050	,008	,274
ROE	,057	-,038	,354	,181	,046	1,000	,140	-,022	-,185	,273
accounts_receivable_turnover	-,288	,085	,175	,102	-,064	,140	1,000	,131	,180	,098
accounts_payable_turnover	,144	,090	-,042	-,070	-,050	-,022	,131	1,000	-,075	-,200
blocked_accounts	-,284	-,049	-,143	,035	,008	-,185	,180	-,075	1,000	,007
n_years	,216	,423	,297	,483	,274	,273	,098	-,200	,007	1,000

Log Determinants

default_non_default	Rank	Log Determinant
non default	10	-,667
default	10	1,009
Pooled within-groups	10	7,584

Test Results

Box's M		324,637
F	Approx.	4,355
	df1	55
	df2	4875,658
	Sig.	,000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2,112[a]	100,0	100,0	,824

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,321	43,144	10	,000

Standardized Canonical Discriminant

Function Coefficients

	Function
	1
current ratio	,245
equity_to_assets	,652
operating_income_to_sales	-,191
EBITDA_to_net_debt	,482
ROA	,051
ROE	,558
accounts_receivable_turnover	,186
accounts_payable_turnover	,025
n_blocked_accounts	-,251
n_years	-,871

Structure Matrix

	Function
	1
equity_to_assets	,475
ROE	,403
n_blocked_accounts	-,386
ROA	,356
current ratio	,315
accounts_payable_turnover	,296
EBITDA_to_net_debt	,251
operating_income_to_sales	,232
n_years	-,189
accounts_receivable_turnover	,135

Functions at Group Centroids

	Function
default_non_default	1
non default	1,214
default	-1,662

Classification Processing Summary

Processed		80
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	0
Used in Output		80

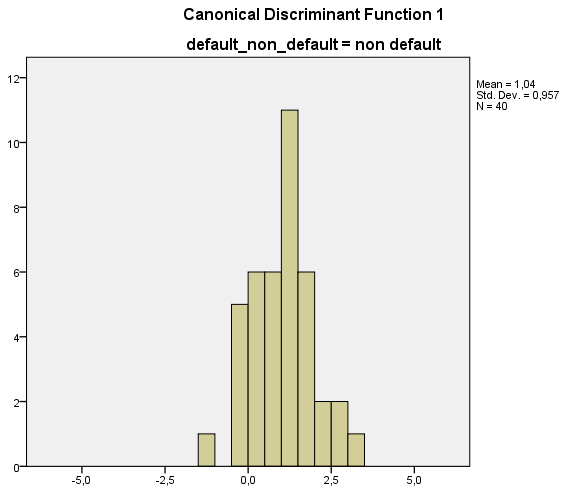
Prior Probabilities for Groups

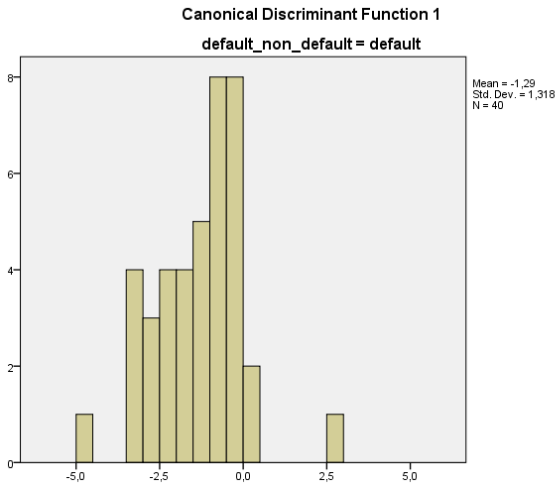
default_non_default	Prior	Cases Used in Analysis	
		Unweighted	Weighted
non default	,500	26	26,000
default	,500	19	19,000
Total	1,000	45	45,000

Classification Function Coefficients

	default_non_default	
	non default	default
current ratio	2,300	1,294
equity_to_assets	-2,141	-8,334
operating_income_to_sales	-1,839	,558
EBITDA_to_net_debt	-2,671	-7,275
ROA	-1,479	-1,980
ROE	-,400	-1,142
accounts_receivable_turnover	,123	,068
accounts_payable_turnover	,311	,296
n_blocked_accounts	,005	,018
n_years	,548	,926
(Constant)	-7,892	-14,287

Separate-Groups Graphs





Classification Results[a,c]

			Predicted Group Membership		
		default_non_default	non default	default	Total
Original	Count	non default	36	4	40
		Default	7	33	40
	%	non default	90,0	10,0	100,0
		Default	17,5	82,5	100,0
Cross-validated[b]	Count	non default	34	6	40
		Default	13	27	40
	%	non default	85,0	15,0	100,0
		Default	32,5	67,5	100,0

a. 86,3% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 76,3% of cross-validated grouped cases correctly classified.

Appendix I: SPSS output for version F

Analysis Case Processing Summary

Unweighted Cases		N	Percent
Valid		45	56,3
Excluded	Missing or out-of-range group codes	0	,0
	At least one missing discriminating variable	35	43,8
	Both missing or out-of-range group codes and at least one missing discriminating variable	0	,0
	Total	35	43,8
Total		80	100,0

Group statistics

default_non_default		Mean	Std. Deviation	Valid N (listwise) Unweighted	Valid N (listwise) Weighted
non default	current ratio	1,2359	,84983	26	26,000
	equity_to_assets	,3181	,25142	26	26,000
	operating_income_to_sales	,0025	,20537	26	26,000
	EBITDA_to_net_debt	,1420	,23981	26	26,000
	ROA	-,0017	,08217	26	26,000
	ROE	,0321	,57558	26	26,000
	accounts_receivable_turnover	9,6294	11,98693	26	26,000
	accounts_payable_turnover	5,6288	6,20519	26	26,000
	n_blocked_accounts	7,8462	22,95682	26	26,000
	n_years	17,6154	6,84150	26	26,000
default	current ratio	,6012	,41555	19	19,000
	equity_to_assets	-,0951	,36211	19	19,000
	operating_income_to_sales	-,1500	,25795	19	19,000
	EBITDA_to_net_debt	-,0753	,37005	19	19,000
	ROA	-,2983	,43764	19	19,000
	ROE	-2,4774	3,27537	19	19,000
	accounts_receivable_turnover	5,9264	4,37544	19	19,000
	accounts_payable_turnover	1,5729	,87402	19	19,000
	n_blocked_accounts	69,5263	81,39026	19	19,000
	n_years	21,2105	6,31206	19	19,000
Total	current ratio	,9679	,76255	45	45,000
	equity_to_assets	,1436	,36354	45	45,000
	operating_income_to_sales	-,0619	,23871	45	45,000
	EBITDA_to_net_debt	,0502	,31697	45	45,000
	ROA	-,1269	,32272	45	45,000
	ROE	-1,0275	2,47956	45	45,000
	accounts_receivable_turnover	8,0659	9,63810	45	45,000
	accounts_payable_turnover	3,9163	5,12779	45	45,000
	n_blocked_accounts	33,8889	62,91741	45	45,000
	n_years	19,1333	6,79104	45	45,000

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
current ratio	,827	8,984	1	43	,005
equity_to_assets	,678	20,456	1	43	,000
operating_income_to_sales	,898	4,871	1	43	,033
EBITDA_to_net_debt	,883	5,709	1	43	,021
ROA	,789	11,490	1	43	,002
ROE	,744	14,762	1	43	,000
accounts_receivable_turnover	,963	1,644	1	43	,207
accounts_payable_turnover	,844	7,953	1	43	,007
n_blocked_accounts	,760	13,562	1	43	,001
n_years	,930	3,233	1	43	,079

Pooled Within-Groups Matrices[a]

	current_ratio	equity_to_assets	OI/sales	EBITDA/NET DEBT	ROA	ROE	accounts_receivable	accounts_payable_	blocked_accounts	n_years
Covariance										
current_ratio	,492	,062	,022	,012	,045	,087	-1,931	,480	-11,056	1,005
equity_to_assets	,062	,092	,013	,021	,061	-,025	,246	,130	-,825	,849
OI/sales	,022	,013	,052	,034	,023	,175	,384	-,046	-1,820	,451
EBITDA/NET DEBT	,012	,021	,034	,091	,016	,118	,295	-,100	,581	,964
ROA	,045	,061	,023	,016	,084	,029	-,177	-,068	,122	,527
ROE	,087	-,025	,175	,118	,029	4,683	2,897	-,227	-22,254	3,916
accounts_receivable	-1,931	,246	,384	,295	-,177	2,897	91,553	5,972	95,534	6,195
accounts_payable	,480	,130	-,046	-,100	-,068	-,227	5,972	22,706	-19,913	-6,299
blocked_accounts	-11,056	-,825	-1,820	,581	,122	-22,254	95,534	-19,913	3079,398	2,636
n_years	1,005	,849	,451	,964	,527	3,916	6,195	-6,299	2,636	43,891
Correlation										
current_ratio	1,000	,293	,137	,058	,222	,057	-,288	,144	-,284	,216
equity_to_assets	,293	1,000	,192	,232	,696	-,038	,085	,090	-,049	,423
OI/sales	,137	,192	1,000	,499	,339	,354	,175	-,042	-,143	,297
EBITDA/NET DEBT	,058	,232	,499	1,000	,187	,181	,102	-,070	,035	,483
ROA	,222	,696	,339	,187	1,000	,046	-,064	-,050	,008	,274
ROE	,057	-,038	,354	,181	,046	1,000	,140	-,022	-,185	,273
accounts_receivable_	-,288	,085	,175	,102	-,064	,140	1,000	,131	,180	,098
accounts_payable	,144	,090	-,042	-,070	-,050	-,022	,131	1,000	-,075	-,200
blocked_accounts	-,284	-,049	-,143	,035	,008	-,185	,180	-,075	1,000	,007
n_years	,216	,423	,297	,483	,274	,273	,098	-,200	,007	1,000

Log Determinants

default_non_default	Rank	Log Determinant
non default	10	-,667
default	10	1,009
Pooled within-groups	10	7,584

Test Results

Box's M		324,637
F	Approx.	4,355
	df1	55
	df2	4875,658
	Sig.	,000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	2,112[a]	100,0	100,0	,824

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	,321	43,144	10	,000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
current ratio	,245
equity_to_assets	,652
operating_income_to_sales	-,191
EBITDA_to_net_debt	,482
ROA	,051
ROE	,558
accounts_receivable_turnover	,186
accounts_payable_turnover	,025
n_blocked_accounts	-,251
n_years	-,871

Structure Matrix

	Function
	1
equity_to_assets	,475
ROE	,403
n_blocked_accounts	-,386
ROA	,356
current ratio	,315
accounts_payable_turnover	,296
EBITDA_to_net_debt	,251
operating_income_to_sales	,232
n_years	-,189
accounts_receivable_turnover	,135

Functions at Group Centroids

	Function
default_non_default	1
non default	1,214
default	-1,662

Classification Processing Summary

Processed		80
Excluded	Missing or out-of-range group codes	0
	At least one missing discriminating variable	35
Used in Output		45

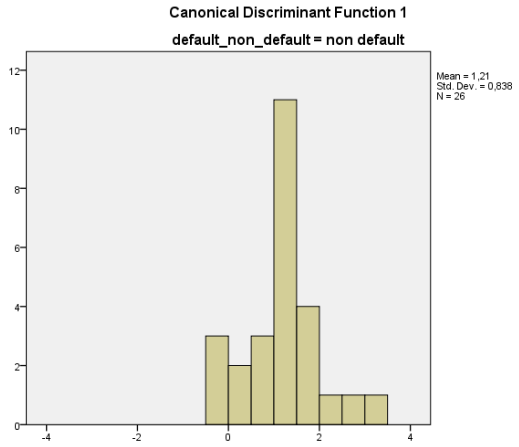
Prior Probabilities for Groups

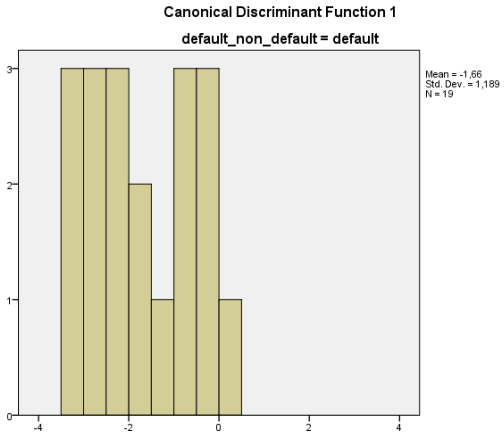
default_non_default	Prior	Cases Used in Analysis	
		Unweighted	Weighted
non default	,578	26	26,000
default	,422	19	19,000
Total	1,000	45	45,000

Classification Function Coefficients

	default_non_default	
	non default	default
current ratio	2,300	1,294
equity_to_assets	-2,141	-8,334
operating_income_to_sales	-1,839	,558
EBITDA_to_net_debt	-2,671	-7,275
ROA	-1,479	-1,980
ROE	-,400	-1,142
accounts_receivable_turnover	,123	,068
accounts_payable_turnover	,311	,296
n_blocked_accounts	,005	,018
n_years	,548	,926
(Constant)	-7,747	-14,456

Separate-Groups Graphs





Classification Results[a,c]

			Predicted Group Membership		
		default_non_default	non default	default	Total
Original	Count	non default	26	0	26
		default	3	16	19
	%	non default	100,0	,0	100,0
		default	15,8	84,2	100,0
Cross-validated[b]	Count	non default	23	3	26
		default	4	15	19
	%	non default	88,5	11,5	100,0
		default	21,1	78,9	100,0

a. 93,3% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 84,4% of cross-validated grouped cases correctly classified.

Appendix J: Povzetek v Slovenskem jeziku

Interna boniteta posojilojemalcev v poslovnih bankah se uporablja za razvrstitev le-teh v različne kategorije oblikovane glede na višino kreditnega tveganja (Crouhy, Galai in Mark, 2001). Tako je na podlagi modela posamezni kategoriji, v katero je uvrščen posojilojemalec, določena verjetnost neplačila posojila. V modele interne bonitete v bankah kot vhodne spremenljivke vstopajo različni indikatorji, ki se delijo na finančne in nefinančne. Po Bessis (2002) finančni indikatorji kvantitativno opisujejo stanje posojilojemalca in so navadno izračunani na podlagi finančnih izkazov, nefinančni pa posojilojemalčevo stanje opredeljujejo kvalitativno in so t.i. »mehki« dejavniki. S področja vpliva finančnih indikatorjev na kreditno tveganje posojilojemalca je bilo narejeno kar nekaj študij, medtem ko Grunert, Noerden in Weber (2005) ugotavljajo, da področje vpliva nefinančnih indikatorjev na izračun interne bonitete ostaja relativno neraziskano. Podatke o nefinančnih indikatorjih je sicer nekoliko težje zbrati, saj so pogosto opredeljeni na podlagi subjektivnih ugotovitev ter v primerjavi s finančnimi, ki jih je moč izračunati iz letnih poročil, manj dostopni.

Pa vendar, ali lahko trdimo, da nefinančni indikatorji predstavljajo dodano vrednost k oceni kreditnega tveganja ter tako njihova vključitev vpliva na večjo natančnost modela, ki izračunava boniteto? To je ključno raziskovalno vprašanje, ki sem si ga postavila v magistrski nalogi. Na podlagi raziskovalnega vprašanja sem opredelila sledečo hipotezo: model, ki je sestavljen tako iz finančnih kot nefinančnih indikatorjev, vodi do bolj natančnih napovedi neplačila podjetja kot model sestavljen samo iz finančnih indikatorjev. Motivacija za raziskavo izhaja iz dejstva, da to področje ni tako akademsko raziskano, prav tako pa sem tudi želela ugotoviti, kako model z različnimi indikatorji (finančnimi ter nefinančnimi) napoveduje plačilo oz. neplačilo podjetja na slovenskem trgu.

Boniteta posojilojemalcev opredeljena z določenim bonitetnim razredom je v bankah pomembno orodje in se uporablja za različne namene. Uporablja se pri kreditnih odločitvah, za izračunavanje kapitalske ustreznosti po IRB (Internal Ratings-Based approach) postopku, za izračunavanje dobičkonosnosti posameznega posla, spremljanje (monitoring) posojilojemalca, analizo dobičkonosnosti kapitala banke ter analizo oblikovanja rezervacij (Treacy in Carey, 2000). Z uvedbo Basla II pa je bankam tudi dovoljeno, da pri izračunu kapitalske ustreznosti uporabljajo svoje interne ocene o stanju posojilojemalcev. Banka, ki se odloči slediti postopku IRB, mora oblikovati model interne bonitete, ki klasificira kreditno izpostavljenost vsakega posameznega posla (Saunders in Allen, 2002).

Kljub temu, da ni veliko akademskih raziskav na temo nefinančnih indikatorjev v bonitetnih modelih, obstaja nekaj študij. Grunert et al. (2005) v svoji raziskavi ugotavljajo, da kombinirana uporaba finančnih in nefinančnih indikatorjev vodi k bolj natančnem predvidevanju neplačila v prihodnosti. Ciampi (2014) je analiziral italijanska majhna podjetja in v analizo vključil nekaj nefinančnih indikatorjev, predvsem s področja korporativnega upravljanja. Ugotovil je, da njihova vključitev v model, izboljša predvidevanje neplačila. Treacy in Carey (2000) sta v svoji študiji ugotovila, da veliko bank kot pomemben nefinančni indikator omenja kvaliteto vodilnega kadra posojilojemalca ter tveganost države, v kateri se posojilojemalec nahaja.

Banke za izračun bonitete posojilojemalca uporabljajo različne modele. Metode na podlagi katerih so zasnovani modeli, so glede na študijo, ki jo je izvedel Basel Committee on Banking Supervision (2000) predvsem: logit in probit, diskiminantna metoda ter klasične tehnike kreditnega tveganje. Sama sem v magistrski nalogi izbrala metodo diskriminantne analize. Raziskavo sem izvedla na naključnem vzorcu slovenskih podjetij, v katerega je vključenih 80 enot, razdeljenih v dve enako veliki skupini. Prva vsebuje enote, ki so bile v času analize na slovenskem trgu aktivne, druga pa enote, ki so bile v času analize v stečaju. Za definicijo neplačila podjetja sem tako izbrala stečaj podjetja, saj je to trenutek, ko je nedvomno jasno, da podjetje ne more več poravnavati svojih obveznosti. Da bi bili skupini čim bolj homogeni, sem izbrala enote podobne velikosti in sicer sem postavila sledeč kriterij izbire: enote so mala in srednje velika podjetja s skupnimi prihodki od prodaje v preteklem letu oz. zadnjem letu pred stečajem, med 1 milijonom evrov in 15 milijonom evrov. Velikost vzorca je delno pogojena z velikostjo slovenskega trga, delno pa drugimi študijami, omenjenimi v nalogi. Vsi podatki, ki sem jih uporabila za izračun indikatorjev, so javno dostopni in sicer v bazah AJPES in GVIN. Pri odločitvi katere indikatorje vključiti v model, sem upoštevala obstoječo literaturo ter ugotovitve iz intervjuja z vodjo oddelka kreditnih odločitev v eni izmed slovenskih bank.

V modelu sem uporabila naslednje indikatorje:

- Kratkoročna sredstva/ kratkoročne obveznosti
- Kapital/ bilančna vsota
- Dobiček iz poslovanja/ prihodki od prodaje
- EBITDA/ neto dolg
- Dobičkonosnost sredstev (ROA)
- Dobičkonosnost kapitala (ROE)
- Obrat terjatev do kupcev
- Obrat obveznosti do dobaviteljev
- Število let podjetja na trgu
- Število dni, ko je imelo podjetje blokiran bančni račun v zadnjem letu

Zbrala in analizirala pa sem podatke tudi za dva dodatna indikatorja:

- Panoga v kateri podjetje deluje
- Konkurenca v panogi v kateri podjetje deluje

Da bi lahko odgovorila na raziskovalno vprašanje, sem s pomočjo programa SPSS sprva naredila dve diskriminantni funkciji, prvo samo z uporabo finančnih indikatorjev, nato pa sem v drugi funkciji dodala še nefinančne indikatorje. V naslednjem koraku sem izločila še odklonske enote, saj je metoda na odklonske enote zelo občutljiva. Tako sem enote pri posameznih spremenljivkah najprej izločila ter jih nadomestila z aritmetičnimi sredinami, v drugi verziji pa sem jih iz analize odstranila ter tako dobila še štiri dodatne diskriminantne funkcije. Rezultate funkcij samo s finančnimi indikatorji ter s kombinacijo tako finančnih kot nefinančnih sem primerjala med seboj.

Najbolj pomembni ugotovitvi moje raziskave sta: (1) model, v katerega so vključeni tudi nefinančni indikatorji, ima višji odstotek pravilnih napovedi ali bo določeno podjetje poravnavalo svoje obveznosti (ali bo šlo v stečaj) tako v primeru vseh enot kot tudi po izločitvi odklonskih enot, (2) model, v katerega so vključeni tudi nefinančni indikatorji, v vseh primerih pojasni večji odstotek variabilnosti med skupinama. Tako zastavljene hipoteze, na podlagi rezultatov, ne moremo zavrnit.

Prav tako pa v analizi ugotavljam tudi, da sta med izbranimi indikatorji najboljša indikatorja za napovedovanje stečaja podjetja število dni, ko je imelo podjetje blokiran bančni račun v zadnjem letu ter višina kapitala, deljeno z bilančno vsoto. Dobri indikatorji za napovedovanje stečaja so prav tako dobičkonosnost kapitala, dobičkonosnost sredstev, kratkoročna sredstva deljeno s kratkoročnimi obveznostmi ter obrat obveznosti do dobaviteljev. Nefinančna indikatorja, ki zaradi svoje narave nista bila vključena v diskriminantno funkcijo, panoga v kateri podjetje deluje ter konkurenca v omenjeni panogi, sta pokazala, da so podjetja v stečaju delovala pogosteje predvsem v panogi C – predelovalne dejavnosti ter panogi F – gradbeništvo. Konkurenca v dejavnosti, izražena kot število subjektov v ožji definiciji dejavnosti (oznaka oredstavlja črko ter pet mestno število), pa ni pokazala razlik med skupino zdravih podjetij ter skupino podjetij v stečaju.

Nadaljnje raziskovanje tega področja je izredno zanimivo, saj se lahko v analizo vključi tudi druge indikatorje ter primerja, kako se odstotek pravilnih napovedi spreminja, prav tako pa se lahko v primeru dostopa uporabi tudi podatke, ki jih zbirajo banke. Tak podatek je na primer število dni zamud pri plačilu obveznosti in se lahko uporabi kot definicija neplačila namesto stečaja podjetja (zamude nad 90 dni). Raziskavo bi se lahko izvedlo tudi z drugo metodo, na primer probit ali logit, ter se nato rezultate primerjalo z rezultati dobljenimi na podlagi diskriminantne analize.