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A Default Prediction Model for

Software Companies

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To my Family

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Chapter 1

Introduction and Research Definition

Dealing with credit risk has been the main issue for lenders since the inception of credit. Banks and other lenders have put great efforts into finding ways to manage or mitigate credit risk. Still, there is common understanding that credit risk cannot be avoided entirely. Research on credit risk has evolved in various techniques for prediction of default and estimation of credit loss. A relatively new approach is the application of statistical methodologies and credit risk models. Today, such models are used by many large financial institutions and have become a standard tool for default prediction in credit risk management.

Credit risk models are based on historical information on defaulted as well as non-defaulted companies. While there is literature supporting the use of qualitative information[1] for the default prediction, such as management skills, leadership style, and business concept, there is also concern about the inherent subjectivity of this approach.[2] Consequently, the majority of credit risk models are based solely on quantitative information, mostly being accounting data.

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[1] Blochwitz, S., Eigermann, J., Unternehmensbeurteilung durch Diskriminanzanalyse mit qualitativen Merkmalen, Zeitschrift für betriebswirtschaftliche Forschung, 52, pp. 58-73
[2] Hayden, E., Modeling an Accounting-Based Rating System for Austrian Firms, 2002, p. 6

However, accounting data does not properly represent the value of companies, as major parts of a company's potential are not reflected by traditional balance sheets.[3] It is the "Intellectual Capital" of a company that cannot be accurately expressed by mere accounting figures. Intellectual capital was defined by Leif Edvinsson as "knowledge that can be converted into value". Terms like "Invisible Balance Sheet" and "Knowledge Management" indicate that one must go beyond accounting data to fully comprehend the true value of a firm.[4] The deficiency of traditional accounting to analyze a company becomes even more pronounced in industries where knowledge represents the key driver of a company. Examples for such industries include the pharmaceutical industry as well as the software industry.[5]

The software industry has experienced unprecedented growth in the recent past. Such growth has resulted in increased need for financing. However, financing software companies is not free of credit risk. The collapse of the formerly praised "New Economy" has evidenced this. It has also been made aware that financial institutions which had to recognize hefty credit losses due to the bankruptcy of software firms, were not capable of understanding the risks involved in financing these companies. Apparently, credit risk was significantly underestimated.

There is no doubt that the software industry continues to have need for financing. It seems also evident, that better techniques are needed to properly predict default of software companies and estimate credit risk involved in lending to these companies. The question is, how should such a default prediction model operate?

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[3] Weber, C.-P, Hörmann, F., "Intellectual Capital - Wissensmanagement", in "Wirtschaftsprüfer-Jahrbuch 2002", Institut Österreichischer Wirtschaftsprüfer, 2002, p. 314

[4] Ibid.

[5] Ibid.

An additional challenge to the banking industry is "Basel II", The New Capital Accord proposed by the Basel Committee on Banking Supervision. Although due for implementation not before the end of 2006, the consultation phase for Basel II started as early as 1999 and banks have been preparing for the new accord since then. Basel II is going to reshape the banking industry in general and risk management in banks in particular. Banks complying with the regulations of Basel II must opt for one of three possible approaches for the estimation of credit risk, which are called the "Standardized Approach", the "Foundation IRB Approach", and the "Advanced IRB Approach". If a bank chooses to opt for one of the IRB Approaches, it will face the requirement of developing a credit risk model which is capable of properly estimating the probability of default for the bank's credit portfolio[6], which may include loans to software companies.

This study covers default prediction for software companies. The ultimate goal of this dissertation is the creation of a model which is strongly geared towards Austrian software companies and is capable of acceptably predicting their default. The quality of results was to be ensured by using consistent data in terms of industry and accounting standards.

Key issues addressed by this dissertation and questions worked on include the following:

1. Can the creditworthiness of a software company in terms of default probability be accurately measured by a credit risk model that is solely based on <u>accounting data</u>? What would the predictive power of such model be?
2. Can the creditworthiness of a software company in terms of default probability be accurately measured by a credit risk model

[6] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 5

that is solely based on qualitative information? What would the predictive power of such model be?

3. Would a combination of quantitative (i.e. accounting data) and qualitative information yield a predictive power stronger than the predictive power of models based solely on either quantitative or qualitative input?

The structure of this dissertation is as follows: Chapter 2 introduces the topic of risk in general and credit risk in particular. The various risks that a bank is facing are discussed and the functions of credit risk management as well as credit risk analysis are explained. The chapter also provides background information on the legal and regulatory framework for credit risk in Austrian banking. Chapter 3 provides a brief overview of traditional credit risk analysis. Chapter 4 discusses credit risk models and explains their application and limitation. Chapter 5 introduces to Basel II. Starting with brief background information on the current capital accord (Basel I), the study explains the necessity of a revision of the current accord and describes the principles of the new accord. Further insight is given into Pillar 1 of the new capital accord, as Pillar 1 will govern the capital requirements and, with this, the credit risk measurement approaches. Impacts of and criticism on Basel II are discussed as well.

Chapter 6 explains the methodology applied for this study. Chapter 7 presents the quantitative model, which was derived solely from accounting data. After the underlying data has been described, the study explains the composition of the financial ratios which provided the basis for the model input. The results of these ratios are subsequently discussed in an explorative manner. This is followed by the calculation of their individual predictive power. Subsequently, the model is created by a stepwise logistic regression, whereby the input of this process are the variables with the strongest individual predictive power. Chapter 8 explains how the qualitative model was created. The process was substantially identical with the process applied for the quantitative model. Chapter 9 examines the effect of combining the quantitative model with the qualitative model. Chapter 10 concludes the dissertation with a summary and a discussion of the findings.

Chapter 2

Principles of Credit Risk

2.1 Types and Nature of Risk in Banks

The origin of the term "risk" is thought to be from the Arabic word "risq" or the Latin word "riscum". As far as the definition of "risk" is concerned, there are numerous suggestions, including "a potential for unwanted negative consequences of an event or activity" and "a measure of probability and severity of adverse effects"[7]. Dominic (1993) distinguishes between systematic (undiversifiable) and unsystematic (diversifiable) risk. While unsystematic risk can be reduced by diversification, systematic risk stays. Consequently, risk cannot be eliminated completely.[8]

Common firm risk can be categorized into business risk, market risk, financial risk, environmental risk, international risk, and political risk.[9] In the financial industry, risk can be classified into balance sheet risk and transactional risk. Balance sheet risk is the risk arising from the mismatch between currency, maturity, and interest rate structure of assets and liabilities. Types of balance sheet risks primarily include

[7] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 79
[8] Dominic, C, Facing up the Risks: How Financial Institutions can survive and Prosper, 1993, p. 3
[9] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 83

liquidity risk, and interest rate risk. Transactional risk is arising from the business transaction a financial institution does and includes operational risk as well as credit risk.[10] The following main risk components can be identified for financial institutions:

2.1.1 Liquidity Risk

This is the risk that a bank does not have enough liquidity to meet the demand for cash from its customers.[11] This may be the case if there are instant and unseasonably high cash withdrawals from depositors due to a loss of confidence in the financial strength of the deposit bank, e.g. when the institution's credit rating fell.[12] In case of a liquidity shortage, banks would have to either borrow additional funds or sell assets. Both steps are costly for the bank, as instant credit is more expensive, if available at all, and a sale of assets under time pressure will most likely result in satisfactory prices for the bank.
If the entire financial market looses liquidity, this is called systematic liquidity risk.[13] Financial markets tend to lose liquidity during periods of crisis or high volatility.[14]

2.1.2 Interest Rate Risk

This term refers to possible losses due to changes in interest rates. Although banks maintain an asset/liability structure which is substantially balanced in terms of maturities, a smaller-scale mismatch occurs frequently. Such mismatch can result in re-investment or re-financing risk. Re-investment risk is the risk that the income on funds which have to be re-invested is lower than the costs

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[10] Saunders, A, Financial Institutions: A Modern Perspective, 1994
[11] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 84
[12] http://www.riskglossary.com/articles_old/glossaryliquidityrisk.htm
[13] An interesting discussion of the Banks´ role within the systematic liquidity risk can be found in Gatev, E., Strahan, P. E., Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market, 2003

of these funds. This may be the case if the tenor of the re-investment is shorter than the tenor of the liability. Re-financing risk, as opposed to Re-investment risk, refers to the possibility that the costs of extending the financing for existing investments are higher and exceed the income on the investments.

2.1.3 Currency Risk

Currency risk is the risk resulting from the fluctuations in currency exchange rates. The more volatile exchange rates the higher is the risk for the bank.

2.1.4 Operational Risk

Also called business risk[15], operational risk is the inherent or fundamental risk of a firm. Operational risk does not address financial risk. In the banking industry, it refers to the risk of loss as a result of a technical failure during the execution or settlement of a transaction.[16] The Third Consultative Paper of The Basel Committee on Banking supervision defines operational risk "as the risk of loss resulting from inadequate internal processes, people and systems or from external events.[17] Examples for such failures can be a breakdown in communications, information or transactional processing or legal/compliance issues, due to technology/systems or procedural failures, human errors, disasters or criminal activity.[18] Operational risk is difficult to quantify. Estimates for operational risk can be based on quantitative and qualitative approaches.[19]

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[14] ibid.
[15] http://www.marketvolume.com/glossary/o0089.asp
[16] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 84
[17] Basel Committee on Banking Supervision, Sound Practices for the Management and Supervision of Operational Risk, 2003
[18] http://www2.bmo.com/content/0,1263,divId-3_langId-1_navCode-3413,00.html
[19] Jovic, D., Piaz, J.-M., Operational Risk Management als kritischer Erfolgsfaktor für Banken, in Der Schweizer Treuhaender, 10/01, pp. 923-930

2.1.5 Credit Risk

This is the most obvious risk a financial institution is facing, representing the risk of a loss due to the default of a customer. Credit risk is as old as lending itself, which means that it dates back as far as 1800 B.C. Hammurabi´s Code, which was written in that time, is said to include sections relating to the regulation of credit in Babylon.[20] There are various categories of credit risk, including:

- Repayment Risk: The risk that the borrower does not repay the loan. In the case of letters of credit, it is the risk, that a bank has made a payment to the beneficiary of the L/C and subsequently does not get reimbursed by the customer for which the L/C had been issued.
- Replacement Risk: The term is used in regards to treasury transactions (e.g. foreign exchange forwards, swaps, etc.). It represents the risk that the customer does not meet its obligation prior to the settlement of the transaction and the bank must replace the customer´s part of the transaction (e.g. delivery of foreign currency) at unfavorable terms.
- Settlement Risk: Risk of a loss during the settlement of a transaction, in case the bank has already executed its part of the transaction and the customer defaults before performing its counterpart of the transaction.
- Issuer Risk: Risk arising from a bank's security underwriting activities, for example a loss in the value of securities temporarily held in the bank's portfolio.
- Secondary Risk: This risk refers to a third party, to which the bank has recourse in case of default of the actual obligor. An example of a third party is a guarantor. It is the risk that the third

[20] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 1

party defaults and the bank loses its ability for a recourse in case of a default of the actual borrower.

- Country risk: Also known as sovereign risk, it is the risk that economic or political change in a country may impact repayments to creditor banks. This risk is considered higher for emerging markets and lesser-developed countries than it is for developed countries.[21]

2.2 Credit Risk Management

Risk management in general is the process of conserving the earnings power and the assets of a company by minimizing the impact of negative unexpected events. The objective of a Risk Manager is therefore to have effective planning of resources needed to recover financial balance and operating effectiveness through the stabilization and minimization of risk costs.[22] The risk management process involves risk analysis (identification), risk assessment (measurement), risk handling, risk management implementation, and risk review.

Credit risk management is the process of managing credit risk in financial institutions. The credit risk manager makes sure that the bank does enter into transactions with an unbalanced risk/return relation. A risk/return relation is unbalanced when the total costs of the credit facility exceed the total return on this facility. The total return on a credit facility comprises interest income plus any credit related fee income. It can be calculated easily. Total cost mainly consists of the following cost components:

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[21] ibid.

[22] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 81

- Direct costs: Costs to establish and maintain a credit facility, e.g. costs of initial due diligence (i.e. initial credit analysis), administrative costs
- Capital costs: According to capital adequacy requirements, banks need to maintain a certain amount of equity for credit risk incurred. The amount of capital required for each credit exposure is dependent on the risk profile of the borrower, the nature of the credit facility, as well as the tenor of the facility.[23] Following the approach of opportunity cost, every credit facility involves costs for the underlying capital.
- Risk costs: Costs of default of the borrower, i.e. principal and interest lost in case of a default. Risk costs are dependent on the expected probability of default, also referred to as "Expected Default Frequency" (EDF)[24], as well as the amount of the credit facility. The expected default probability is being determined through a credit risk analysis process and is usually expressed by a rating.

In contrast to total return, total costs of a credit facility cannot be computed precisely, but rather must be estimated, given unknown actual risk costs. Such costs, however, are usually the driver of the risk/return relation. Consequently, the determination of the appropriate default risk is key in the risk management process.

Default can be defined in various ways. In general, it is considered the failure to perform according to an agreement or obligation. With regard to credit default, it refers to the lack of accurate performance under a financial obligation. Types of credit defaults include the payment default and the technical default. While a payment default refers to the non-payment of interest or principal, a technical default

[23] Bank Austria Creditanstalt AG, Unternehmensfinanzierung im Wandel: Der Weg vom Kreditmarkt zum Kapitalmarkt, 2003, p. 17
[24] More specifically, EDF refers to the risk of a default of a customer within one year

is non-compliance with one or more terms of a credit agreement[25]. However, a lender may realize a loan loss even before an actual payment default occurs. This is the case if the bank is expecting a future payment default of its borrower due to a deterioration in the borrower's creditworthiness.

According to the Basel Committee on Banking Supervision (2003)[26], a default has occurred with regard to a particular obligor when either or both of the two following events has taken place:

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held)
- The obligor is past due more than 90 days on any material credit obligation to the bank.

Risk and reward management is the core skill responsible for success of financial institutions.[27] A comprehensive and strategic approach to risk management should therefore be chosen.[28] FIRM, which stands for "fully integrated risk management", is such an approach. Accordingly, risk management should be approached on an institution-wide basis using policies, procedures, and reporting mechanisms to identify risk at any level in the organization.[29]

[25] http://www.defaultrisk.com/glossary_d.htm
[26] Basel Committee on Banking Supervision, Third Consultative Document, Bank for International Settlements, 2003
[27] Dominic, C, Facing up the Risks: How Financial Institutions can survive and Prosper, 1993, p. 3
[28] Williams, E. J., Risk Management Comes of Age, Journal of commercial Lending, January, 1995
[29] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 83

2.3 Legal and Regulatory Framework

Banks operating in Austria have to comply with the "Bankwesen-gesetz" (BWG), which is the Austrian Banking Act. It represents the legal framework for banking in Austria. The BWG contains certain rules for credit risk management[30]. Paragraph 27 (7) BWG calls for a comprehensive risk analysis through banks. Accordingly, Austrian banks have to analyze the financial condition of the prospective borrower and request disclosure of the borrower's financial statements to the bank prior to granting the credit as well as subsequently over the entire life of the credit[31].

Given the obligation of a comprehensive credit analysis, the bank not only need to analyze the financial statements but also need to request credit-sensitive information beyond the borrower's financial statements.[32] Consequently, basing the credit decision solely on the information provided by the financial statement would not be sufficient according to BWG. In fact, the credit decision is to be made after a in-depth credit analysis is performed.

2.4 Credit Risk Analysis

Credit risk analysis is the process through which a bank assesses the credit risk involved in a prospective or existing transaction that exposes the bank to credit risk. The credit analysis ultimately results in an estimation of the likelihood of a default of the customer. Typically, this expectation is expressed in a grading called "credit rating". People performing credit analyses are referred to as "credit

[30] Bruckner, B., Neue Wege in der Bonitätsbeurteilung von Firmenkunden - Konzept zur Entwicklung eines integrierten Systems, 1996, p. 27
[31] Par. 27 (7) BWG
[32] Bruckner, B., Neue Wege in der Bonitätsbeurteilung von Firmenkunden - Konzept zur Entwicklung eines integrierten Systems, 1996, p. 28

analysts" and require a variety of skills as well as a great deal of experience. Credit analysis entails human judgement.

Credit analysis which is geared towards analyzing quantifiable performance is called "quantitative credit analysis". Quantitative credit analysis uses financial information derived from company balance sheets and income statements. In contrast to quantitative credit analysis, "qualitative credit analysis" is referred to as the art of analyzing unquantifiable performance. Qualitative analysis is sometimes called "strategic analysis".[33]

2.5 Limitations of Credit Risk Analysis

Credit analysis has several limitations. First of all, a credit analysis expert system of this kind is expensive to develop and maintain. Much time and experience is needed to create a complete credit analysis system. As business environment and economy are changing constantly, the systems must be reviewed regularly and adapted accordingly. Employees who are supposed to work with this system need to be trained. As new employees join the bank and the existing staff needs to be kept updated to changes to the credit analysis system, training has to be provided on an ongoing basis.

Credit problems can result from poor execution. Although a bank may have a highly developed credit analysis system and may provide appropriate credit training, credit problems often arise in a transaction which were insufficiently or wrongly analyzed. This may be caused by either negligence or a basic lack of talent.[34]

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[33] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 87
[34] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 90

Reliance on financial statements can be deceptive, as financial reports can be obsolete by the time they arrive at the bank. Furthermore, the reported numbers may provide little insight into the true risks that the company faces. Credit analysis has also often lulled banks into a false sense of security, failing to protect them against systematic risks embedded in their business.[35] Such systematic risks include portfolio concentration, which means that the bank's exposure to a certain industry is disproportionately high compared to the size of its total portfolio.

As a matter of fact, credit risk cannot be avoided completely. Even if a bank were to invest solely in treasury bonds from highest-rated governments, a certain extent of credit risk remains - although in this case a very small one. Given the inability to rule out credit risk entirely, a bank must strive for a comprehensive and state-of-the-art credit risk management system. Credit risk is manageable, but only if it can be identified and monitored appropriately.

[35] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 89

Chapter 3

Traditional Credit Risk Analysis

An in-depth credit risk analysis is a lengthy and complex process. Each bank has its own way of analyzing the creditworthiness of customers. This is primarily due to their different market approaches and therefore different customer portfolios. Depending on how the banks´ portfolio is structured in terms of industries, average company size, average company risk profile (e.g. investment grade versus non-investment grade[36]), the financial institutions are sensitive to different changes in the economic environment. Consequently, each bank has its own set of areas, which are emphasized during a credit risk analysis. However, there are many similarities. A traditional credit analysis typically includes the following steps:[37]

3.1 Purpose of the Loan

The initial question an analyst has to answer is about the purpose of the loan. Typically, financing needs are related to capital expenditure, working capital expansion, or acquisitions. Commercial banks usually decline requests for funding of operating losses due to increased credit risk.

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[36] Investment grade refers to companies which are rated by Standard & Poor´s and/or Moody´s and were assigned a rating of at least BBB (Standard & Poor´s) or Baa (Moody´s).
[37] also compare with Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 84

3.2 Financial Analysis

As a next step, the company's balance sheet and profit and loss statement are analyzed in order to assess the financial position of the prospective obligor as well as to identify trends. A financial analysis usually includes the spreading of the financial statements with internal spreading tools, which facilitate the assessment by calculating financial ratios.[38] Additionally, the credit analyst may perform a financial projection, which is designed to determine the company's future capacity for loan repayments, based on the projected cash flow generation.

3.3 Industry Analysis

edit analysis also involves an analysis of the industry in which the customer operates. This is based on the likelihood, that a company's business will be affected by its industry, both in a positive and a negative way. The industry analysis includes an assessment of the current state of the industry as well as the identification of industry trends. Each industry has its own unique structure and dynamics. A firm's position is affected by the level of maturity of its industry. While a growing industry generally offers growth opportunities to the company, a mature industry is characterized by market saturation, a lack of significant growth potential, and price pressure as a result of fierce competition.[39]

Furthermore, the credit analyst evaluates the competitive position of the company and compares the development of the prospective

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[38] Another application of financial ratios has traditionally been in valuation of companies. See Wagenhofer, A., Hoermann, F., Berichterstattung ueber wertorientierte Unternehmensfuehrung, in: Institut Österreichischer Wirtschaftsprüfer (Hrsg.): Wirtschaftsprüfer- Jahrbuch 2001

[39] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 88

borrower with the development of its direct competitors. These direct competitors are usually referred to as the "peers".[40]

3.4 Soft Facts

The credit analysis also covers credit sensitive areas of the company, which cannot or can hardly be made quantifiable. Due to a lack of quantifiable measures - the so called "hard facts" - these areas are known as the "soft facts" of the company. There is a broad variety of soft facts that are evaluated by banks during the credit analysis process. Different banks have different areas they put emphasis on for their overall judgement. Typical areas evaluated include management skills, business strategy, employee skills, internal organization, quality of products or services, quality and reliability of financial accounting and reporting, and information policy toward the bank.

Soft facts have in common that they are difficult to evaluate given the lack of quantifiability. Consequently, the evaluations being made by credit analysts are subjective. To ensure a certain extent of objectivity and comparability, banks usually create guidelines, so-called "rating rules", which provide guidance to the credit analysts. Still, evaluation and measurement of unquantifiable performance is a complex task and is being approached in different ways.

[40] for an introduction into industry analysis see Bruckner, B., Neue Wege in der Bonitätsbeurteilung von Firmenkunden - Konzept zur Entwicklung eines integrierten Systems, 1996

Chapter 4

Credit Risk Models

Over the last 30 years, new techniques of credit risk analysis have evolved which were prompted by a number of market forces, including the following:[41]

- Deregulation of financial markets, which has resulted in new lenders entering the market and providing services
- Shift from balance-sheet lending, i.e. lending based on underlying collateral, to cash flow lending
- Increase in off-balance sheet risks
- Rationalization of the risk management process, driven by deteriorating income due to shrinking loan margins
- Securitization, which has prompted the development of more efficient credit risk tools
- Advances in finance theory, which have provided new ways of approaching credit risk

Tools from statistics and operations research have contributed to the progress in credit risk measurement. The question to be answered has remained the same, being: Given past experience, what is the likelihood of default?

[41] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 102

4.1 Statistical Methods

Statistical methods, also referred to as econometric techniques, model the probability of default as a dependent variable whose variance is explained by a set of independent variables. The independent variables can include quantitative data (e.g. financial ratios) and/or other indicators, such as soft facts.

4.1.1 Linear Discriminant Analysis

Linear discriminant analysis is used both in the form of a univariate as well as a multivariate analysis. Univariate discriminant analyses are commonly based on accounting information. Credit analysts compare various key accounting ratios of borrowers with industry or group norms and trends for these variables. Purpose of the analysis is to determine if there is a significant departure of the borrower's ratios from the norm for its industry.

One of the founding works in this field was performed by Beaver (1966)[42]. He used financial ratios in a univariate prediction model in order to examine the prediction of financial distress. His work intended to provide empirical verification of the usefulness of accounting data for prediction purposes. Beaver used a sample of 79 failed and non-failed companies and designed a sample, where he paired each failed company with a comparable non-failed company. A firm was considered "failed", if it had met one of the following criteria: bankruptcy, bond default, overdrawn bank account or non-payment of dividend on preferred stock. [43]

[42] Beaver, W. H., Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111, 1966
[43] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 34

For each of the companies selected for his work, Beaver computed thirty ratios for five consecutive years and grouped them into six categories. These categories were: cash flow, net income, debt to total assets, liquid assets to total assets, liquid assets to current debt, and turnover ratios. Of each category, one ratio was selected and included in the univariate prediction model. Overall, Beaver found cash flow and debt to equity ratios to be good indicators. He observed that ratio analysis can be useful for at least five years before default. He also found that not all ratios had the same predictive power. Beaver also performed a dichotomous classification test. Furthermore, in a third approach, he used ratios to assess the likelihood of failure by examining histograms.[44]

In general, ratios measuring profitability, liquidity, and solvency were identified as most significant predictors in the various univariate studies performed since. However, the order of their importance was unclear, as studies suggested different ratios as the most effective indicators for possible financial distress. As a logical enhancement of the univariate analyses, researchers tried to combine the findings from these studies to a meaningful predictive model. The key questions in creating such model where:

a) Which ratios are most important in detecting bankruptcy potential?

b) What weights should be attached to these selected ratios?

c) How should the weight values be objectively established?[45]

In 1968, Altman presented the Z-score model, a multivariate approach, which was based on the values of univariate measures. Altman designed a sample of 66 firms, covering a time span from 1946 to1965. A multivariate discriminant function was developed

[44] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, pp. 35-36

[45] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 115

which best discriminated failed and non-failed companies. Similar to Beaver, Altman used a paired sample based on size and industry and applied 22 ratios, which had been grouped into five categories, namely liquidity, profitability, coverage, solvency, and activity. From the original 22 variables, the final model chosen included 5 ratios.

4.1.2 Logistic Regression

The goal of logistic regression is to correctly predict the category of outcome for individual cases using a model. To accomplish this goal, a model is created that includes predictor variables that are useful in predicting the dependent variable. Several different options are available during model creation. Variables can be entered into the model in the order specified or logistic regression can test the fit of the model after each coefficient is added or deleted. Such approach is referred to as stepwise regression[46].

The advantage of logistic regression over the linear discriminant approach is no requirement that the predictor variables follow a multivariate normal distribution.[47] While univariate and multivariate discriminant analyses are still in use, recent researchers seem to be in favor of logistic regression analysis, which has become commonly used in credit risk analysis.[48]

Studies published in the recent past using a logistic regression as an approach for credit risk modeling includes the work of Hayden (2002)[49]. Hayden used 65 variables and a data sample on Austrian companies to create a rating model, which was solely based on

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[46] http://online.sfsu.edu/~efc/classes/biol710/logistic/logisticreg.htm
[47] Boonyanunta, N., Zeephongsekul, P., State of the Art Credit Risk Analysis Model: Comparative Analysis between Statistical Approaches and Neural Network Approaches, 2000
[48] Boritz, J. E., Kennedy, D. B., Effectiveness of neural network typs for prediction of business failure, Expert Systems with Application 9 (4), pp 503-512
[49] Hayden, E., Modeling an Accounting-Based Rating System for Austrian Firms, 2002

accounting ratios. One main purpose of this study was to provide a benchmark for Austrian banks for the adaptation of their rating models to the new guidelines of the Basel Committee on Banking Supervision (Basel II).

4.1.3 Neural Networks

A relatively new approach to credit risk classification[50] is the application of neural network analysis[51]. Such artificial neural networks were developed from studies of biological neurons.[52] Applications of neural networks to distress prediction analysis include Coats and Fant´s[53] application to corporate distress prediction in the U.S., and Altman, Marco, and Varetto´s[54] application to corporate distress prediction in Italy. An application to consumer loans and home mortgages was presented by Trippi and Turban.[55]

4.2 Theoretical Models

A new development in credit risk analysis is the approach via the stock price of a company[56]. This approach is based on option pricing methods and Merton´s approach to default probability.[57] The main idea is that the capital market is perfectly knowledgeable about credit

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[50] For a comparative technical discussion of these methods refer to Boonyanunta, N., Zeephongsekul, P. (2000)
[51] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 128
[52] Boonyanunta, N., Zeephongsekul, P., State of the Art Credit Risk Analysis Model: Comparative Analysis between Statistical Approaches and Neural Network Approaches, 2000
[53] Coats, P., Fant, K., Rocognizing Financial Distress Patterns Using A Neural Network Tool, Financial Management 22 (3), pp 142-155
[54] Altman, E. I., Marco, G., Varetto, F., Corporate Distress Diagnosis: Comparisons Using Linear Discriminant Analysis and Neural Networks. Journal of Banking and Finance 18 (3), pp 505-529
[55] Trippi, R. R., Turban, E., Neural Networks in Finance and Investing, 1996
[56] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, p. 129
[57] Merton, R. C., On the Pricing of Corporate Debt: The Risk Structure of Interest Rates, Journal of Finance 29, pp. 449-470

sensitive information. The stock price of a company is therefore a function of the individual buy/sell decisions of investors, which in turn are based on their information on the company. Falling stock prices thus indicate a deterioration of the company's financial condition. Studies have confirmed that the capital market revises downwards its valuations of failing companies well before the bankruptcy actually occurs. Related research as cited by Foster (1986)[58] includes the works of Aharony, Jones, and Swsary (1980), Petteay and Sinkey (1980), Shick and Sherman (1980), Altman and Brenner (1981), and Clark and Weinstein (1983). A more recent study was performed by Tudela and Young (2002)[59]. The leading example of stock market-based credit measures is the expected default frequency model of KMV[60]. Credit risk tools like KMV have become increasingly popular in international banking.

The KMV model calculates the "Expected Default Frequency" (EDF) in a three step approach. First, the market value and the volatility of the company are estimated from the market value of its stock, the volatility of its stock, and the book value of its liabilities. In a second step, the firm´s default point is calculated from the firm's liabilities. Also, an expected firm value is determined from the current firm value. Using these two values and the firm's volatility, a measure is constructed that represents the number of standard deviations from the expected firm value to the default point. This point is called "distance to default". Thirdly, a mapping is determined between the distance to default and the default rate, based on the historical default experience of companies with different distance-to-default values.[61]

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[58] Foster, G., Financial Statement Analysis, 1986, pp. 558-559
[59] Tudela, M., Young, G., A Merton-model approach to assessing the default risk of UK public companies, 2002
[60] KMV is a subsidiary of Moody´s (rating agency) that sells credit analysis software.
[61] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 143-144

4.3 Application of Credit Risk Models

Credit risk models are widely used in commercial banks.[62] One major area of application is the determination of default probability and assignment of a risk rating. While most of the banks using a credit risk model for rating purposes rely exclusively on such rating, some institutions use the model to challenge the rating assigned by the traditional credit analysis process.[63]

Once determined, the default probability is the basis for a number of other decisions to be made in commercial lending. First of all, the core question of either granting or declining the credit must be answered. Furthermore, the pricing on the credit is driven by the expected default probability. As explained in chapter 2.2, the bank is unlikely to enter in a new credit exposure if the total income on the facility is not sufficient to cover the estimated total costs of the exposure. Therefore, the higher the EDF, the higher the pricing on the credit facility.

Areas of application include credit portfolio management, where models are used to select assets, i.e. existing credit facilities, from a pool to construct a portfolio acceptable to investors or to achieve the minimum credit quality needed to obtain the desired credit rating.[64] Once a portfolio is constructed, it is typically transferred to a separate legal entity[65] and sold to investors.

Later on, in case the bank has decided to enter into the credit transaction and the loan has been granted, credit risk models are

[62] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 54
[63] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 105
[64] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 105

used in the annual review process to re-assess the risk profile of the borrower and re-evaluate the accuracy of the assigned rating. Models can also be used for early warnings of potential financial problems of the borrower. Studies indicate, that, as early as three to five years prior to default, the ratios of bankrupt companies start to exhibit a behaviour that is different than the one of non-defaulted companies.[66]

Credit risk models are also used by investors, who evaluate the feasibility of an investment into credit securities, such as bonds, loans[67], or aforementioned credit portfolios. Furthermore, similar models can be used by auditors, who make judgments on the going concern of a company. A related study about the application of a statistical model for audited purposes was made by Koh and Killough (1990).[68] Other parties using credit risk models include the company's management, as well as regulatory bodies and government authorities.

4.4 Criticism on Credit Risk Models

Given non-linearity of actual data, credit risk models such as the linear discriminant analysis that assume linearity may fail to accurately predict corporate failure.

Accounting-based statistical models have been criticized for various reasons:

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65 Such entities are often referred to as Special Purpose Vehicles (SPV), as they are exclusively set up to serve one special purpose.
66 Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 55
67 Typically, investors are looking for medium-term or long-term loans to invest in. Given long-term tenor and usually fixed income, such loans are not very different from bonds. Main difference is that bonds are publicly traded.
68 Koh, H. C., Killough, I. N., The Use of Multiple Discriminant Analysis in the Assessment of the Going-concern Status of an Audit Client, Journal of Business Finance and Accounting, 1990

a) Book value is historical: Since book values represent historical values, models based on book values fail to capture fast-moving changes in the financial condition of the borrower. If market values were applied, such changes would be reflected in a more timely manner.[69]

b) Accounting data is incomplete: Accounting data does not always provide a complete picture of the company's real condition[70]; for example indebtedness in case of off-balance sheet financing: any model based on accounting data that has not been adjusted for off-balance sheet debt, must necessarily produce imprecise results.

c) Book value does not represent market value: For various reasons, there can be a gap between the book value of an asset and its market value (e.g. real estate). In case the market value of a company's assets exceed their book value, a model that computes the risk profile of a company on the basis of its book values consequently understates the financial condition of the firm.

d) Certain values are not included in the balance sheet: Significant values of a company are not reflected in its balance sheet. One such value is "Intellectual Capital"[71]. The company value is therefore not properly reflected by an accounting-based model.

e) Different accounting methods:[72] The picture of a company as presented by its financial statements is somewhat dependent on the accounting standards the company has used to prepare its financial statements.[73] In the case of Goodwill, which sometimes accounts for a significant portion of a firm's assets, the respective

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[69] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 134

[70] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 134

[71] Weber, C.-P, Hörmann, F., "Intellectual Capital - Wissensmanagement", in "Wirtschaftsprüfer- Jahrbuch 2002", Institut Österreichischer Wirtschaftsprüfer, 2002

[72] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 32

accounting methodology can heavily affect the firm's financial position. Another interesting example - even more for this study - is software[74].

f) Industry specific balance sheet structures: Balance sheet structures vary among industries. A software company will naturally have a different asset structure than a property development firm. Consequently, the higher the number of different industries in a sample which is used to create a rating model, the more imprecise its results will necessarily become. The best results in terms of accurate predictability are produced if the model is tailor-made for companies of just one industry.

g) Seasonality: As credit risk models are based on fiscal year end financials, it may be improper to apply such model on interim financial statements of a company in a seasonal industry, since balance sheet structures can vary along with the business cycle.

h) Start-ups: Companies, which have not yet prepared financial statements (start-ups) can not be examined at all with accounting-based models[75].

4.5 Measuring Predictive Power

Predictive power in general is the ability of a hypothesis or model to predict unobserved effects[76]. With regard to credit risk, it is the ability of a variable (e.g. result of a financial ratio) or rating model to distinguish between defaulted and non-defaulted companies. This ability to distinguish between defaulters and non-defaulters, also

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[73] Fischer, T., Vielmeyer, U, Bilanzierung der Aufwendungen für die Erstellung von Internetauftriten nach US-GAAP, IAS und HGB

[74] For a discussion of accounting for software under different accounting standards see Pirker, S., Bilanzierung von Software beim Hersteller unter Berücksichtigung Internationaler Rechnungslegungsvorschriften, 1996

[75] Chijoriga, M. M., An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania, 1997, p. 32

[76] http://www.astro.virginia.edu/~jh8h/glossary/predictive.htm

referred to as discriminatory power, is a key requirement for the precision of a rating system in general[77].

There are several statistical methodologies to measure the predictive power. Widely used models include the "Cumulative Accuracy Profiles" (CAP), also referred to as the "Power Statistic"[78], and the "Receiver Operating Characteristic" (ROC).

4.5.1 Cumulative Accuracy Profile

The concept of CAP is that all companies are ordered according to the score, respectively the result of the variable, beginning with the company with lowest score (or the worst result) and ending with the company with the highest score (or the best result). For a given fraction x of the total number of companies the CAP curve is constructed by calculating the percentage d(x) of the defaulted companies whose scores are equal to or lower than the maximum score of fraction x. This is done for x ranging from 0% to 100%.

A perfectly predictive variable will have the lowest results for the defaulters. In this case the CAP curve is increasingly linear and then stays at one. For a random model with zero discriminatory power the fraction x of all companies with the lowest results will contain x percent of all defaulted companies. In practise, the predictive power will be somewhere in between those two extremes[79]. The following figure illustrates the concept:

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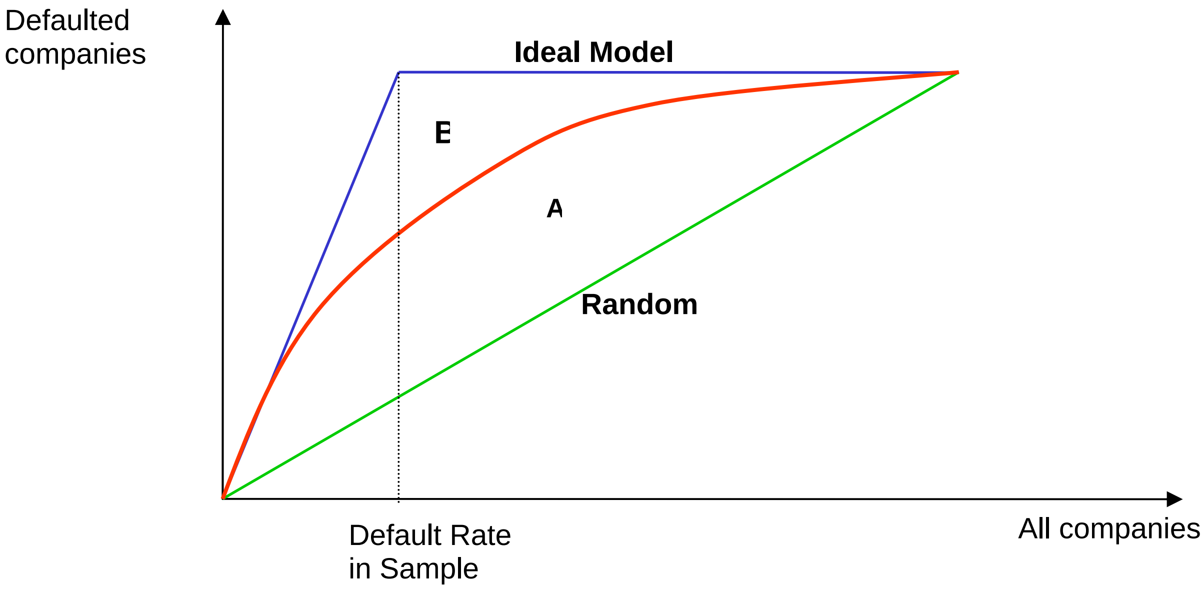
[77] Hamerle, A., Rauhmeier, R., Rösch, D., "Uses and Misused of Measures for Credit Rating Accuracy", 2003
78 Liebig, T, Nyberg, M, Testing Results of Credit Monitor (KMV) for listed German Companies, Deutsche Bundesbank, 1999
[79] Hayden, E., Modeling an Accounting-Based Rating System for Austrian Firms, p. 80, 2002

Figure 4.1: Cumulative Accuracy Profile (CAP)



A: Area between CAP curve of validated variable and CAP of random variable
B: Area between CAP curve of ideal variable and CAP or random variable

The predictive power of a variable is measured by the "Accuracy Ratio" (AR), which is defined as the ratio of the area between the CAP curve of the variable being validated and the CAP of the random variable and the area between the CAP curve of the perfect variable and the CAP curve of the random variable. Therefore, the higher the AR of a variable and the closer to 1, the stronger its predictive power. A random variable with no predictive power will have an AR of 0. An AR of 1 therefore means that 100% of the area under the CAP curve of the ideal variable is covered by the area under the CAP curve of the variable being validated. The AR can also be negative. This means that the variable does still have predictive power, but the defaults occurred at companies where the result of the variable was higher than the average of the sample. As opposed to a positive AR, which indicates that the lower the result of the variable, the higher the default frequency, a negative AR indicates that the higher the result of the variable, the higher the default frequency.

4.5.2 Receiver Operating Characteristic

This method was introduced by Peterson, Birdsall, and Fox[80], and was applied to psychology by Tanner and Swets[81]. It has also been in use in other fields, e.g. in medicine[82]. Later on, it was used for validating internal rating models, which was suggested by Sobehart and Keenan[83]. They argued that the size of the area under the ROC curve can be used as an indicator for the quality of a rating model.

While the concept of the ROC is very similar to the CAP, one main difference is the definition of the crucial area, the so-called Area Under the ROC Curve (AUROC). The AUROC is defined as the ratio between the ROC curve (= equivalent to CAP curve) of the variable being validated and the ROC curve of the random variable and the area between the ROC curve of the perfect variable and the ROC curve of the random variable.

The AUROC can have values between 100 and 0, but cannot be negative, as the x-axis is the lower limit.

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[80] Peterson, W., Birdsall, T., Fox, W., The Theory of Signal Detection, IRE Professional Grop on Information Theory, PGIT-4 pp. 171-212, 1954

[81] Tanner, W., Swets, J., A Decision-Making Theory of visual Detection, Psychological Review 61, pp 401-409, 1954

[82] Hanley, A., McNeil, B., The Meaning and Use of the Area Under a Receiver Operating Characteristics (ROC) Curve, Diagnostic Radiology 143, pp 29-36

[83] Sobehart, J., Keenan, S., Measuring Default Accurately, Credit Risk Special Report, Risk 14, pp 31-33, 2001

Chapter 5

Credit Risk and Basel II

Credit risk management in Austria as well as internationally is about to be reshaped by the implementation of the New Basel Capital Accord, commonly referred to as "Basel II", which has been proposed by the Basel Committee on Banking Supervision ("The Committee"). The Basel Committee was established by the central-bank Governors of the Group of Ten Countries ("G10") at the end of 1974. The Committee's members now come from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Spain, Sweden, Switzerland, United Kingdom and United States. These countries are represented by their central bank and also by the respective banking supervisory authority. The Committee does not have any formal supranational supervisory nor do its conclusions have legal force. Rather, the Committee establishes supervisory standards and guidelines and recommends their implementation through individual authorities of countries.

Basel II is a revision of the currently effective 1988 Basel Capital Accord ("Basel I") which has been adopted by different banks in more than 100 countries. Initially, the focus of this accord had been on internationally active banks in the G10 countries.

5.1 Current Capital Accord: Basel I

Basel I as the currently effective capital accord is considered insufficient for today's complex financial system is and being criticized for three major shortcomings:

a) Too simplistic: Basel I is considered too simplistic to adequately address the activities and risks of the complex international financial system. Bank assets are categorized into one of only four categories, each of which represents a certain risk class and having a certain risk weight. The minimum capital requirement is calculated by multiplying the risk weight by 8 percent. Sovereign risk is weighted with either zero or 100% percent[84], intra-bank exposure is weighted with 20%, and mortgage loans are weighted with 50%. All other exposure, however, is weighted with 100% regardless of the credit risk involved. Consequently, a bank must set aside the same amount of capital for a very strong borrower, as it must for a very weak customer.[85] This lack of differentiation among the degrees of risk results in uninformative or misleading capital ratios.[86]

b) Not state-of-the-art: Risk management and the determination of capital required have evolved beyond the state-of-the-art at the time when Basel I became effective. Since then, banks have themselves developed new techniques to improve their risk management and internal measures to determine economic capital.[87]

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[84] OECD members have a zero percent risk weight, regardless of their likelihood of defautl, while non-OECD members have have a 100% risk weight. See also Cooper, L., The dawn of a new era, Risk Magazine, Oct. 1999

[85] The realtive insensitivity of the current accord to risk was evidenced by the QIS3 results, as described later in this study.

[86] Ferguson, R. W., Testimony before the Subcommittee on Domestic and International Monetary Policy, Trade, and Technlogy, committee on Financial Services, U.S. Huse of Repesentatives, February 27, 2003

[87] Ibid.

c) Increased Heterogeneity and Concentration in Banking: The banking industry has developed increasingly sophisticated and heterogeneous products and services . At the same time, consolidation in global banking has led to increased concentration. A significant weakness or failure of one of these large entities could severely damage the global financial system and have macroeconomic consequences. Basel I is considered to be not appropriately addressing these developments.[88]

Given the defects of the current capital accord, there is common understanding that a new Capital Accord is needed.[89]

5.2 Principles of Basel II

The underlying rationale for the development of the New Basel Capital Accord is that safety and soundness of the global financial system can only be secured by the combination of effective credit risk management, banking supervision, and market discipline.[90] Essentially, the proposals focus on making the capital requirements for banks more strongly dependent on Economic Risk as well as taking into account recent developments in the financial markets and in the institutions' risk management. Basel II also represents a framework for credit risk management, that intends to align regulatory capital requirements more closely with underlying risks, and to provide banks and their supervisors with several options for the assessment of capital adequacy.[91]

Although Basel II focuses primarily on internationally active banks, the Committee expects the New Accord to be adhered to by all

[88] Ibid.
[89] Swibel, M., Business In The Beltway: Basel II Banking Brouhaha, Forbes Magazin, April 2, 2003
[90] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 4

significant banks worldwide.[92] While the European Union (EU) plans to apply Basel II to all banks, U.S. authorities have decided to limit the application of Basel II to a few internationally active American banks.[93] Banks, which will be required to adopt Basel II include, among others, Citigroup, J.P Morgan Chase, Wells Fargo, Bank One, SunTrust, and BB&T.[94]

The proposal is based on three mutually reinforcing pillars that allow banks and supervisors to evaluate the various risks that banks face.

5.2.1 Minimum Capital Requirements - Pillar 1

Pillar one seeks to refine the measurement framework set out in the 1988 Accord. The intention is to have a clear-cut differentiation in credit risk ratings. The ratings directly affect pricing as well as the requirement for underlying equity capital. Furthermore, risk-mitigating instruments, i.e. credit collateral, are recognized more precisely. All this will be achieved by differentiated approaches to the measurement of credit risk. Additionally, operational risks are taken into consideration.[95] Basel II sets out options from which banks, with the authorisation of their supervisor, can choose depending on the complexity of their business, as well as the quality of their risk management.

A standardised approach for credit risk - building upon the 1988 Accord and introducing the use of external credit assessments - will be available for less complex banks. Banks with highly developed

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[91] Press release of the Basel Committee on Banking Supervision, January 16, 2001
[92] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 4
[93] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 4
[94] Swibel, M., Business In The Beltway: Basel II Banking Brouhaha, Forbes Magazin, April 2, 2003
[95] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 5

risk management systems, which meet certain supervisory standards, can opt for an internal ratings-based approach. Under this approach, main components of credit risk, such as the default probability, will be estimated internally by a bank.[96]

The Committee has also proposed a capital charge for operational risk. With respect to the overall level of capital, the Committee aims to provide a more risk-sensitive methodology that on average neither raises nor lowers regulatory capital for banks, after including the new operational risk capital charge. However, based on the risk profile of the bank, the banks´ individual capital requirements may increase or decrease.

The capital requirement is calculated as follows:[97]

$$\boxed{r * A = RWA \Rightarrow RWA * 8\% = RC}$$

r = risk weight
A = Assets
RWA = risk-weighted assets
RC = regulatory capital

5.2.2 Supervisory Review Process - Pillar 2

Proposals with respect to Pillar 2 include a strengthening of supervisory bodies. An institution's capital adequacy as well as the internal assessment process will be reviewed by a supervisory body.

[96] Press release of the Basel Committee on Banking Supervision, January 16, 2001
[97] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 4

5.2.3 Market Discipline - Pillar 3

Pillar 3 aims at improving market transparency. Uniform market transparency shall be ensured through effective disclosure rules, which cover the risk profile as well as control and management systems.[98]

5.3 Minimum Capital Requirements

The Basel II proposal for determination of the minimum capital requirement is directly affecting the credit risk measurement and rating approach that banks must apply going forward. Therefore, the related proposals shall briefly be discussed.

The proposal for the calculation of minimum capital required is based on the concept of a capital ratio where the numerator represents the amount of capital a bank has available and the denominator is a measure of the risks incurred by the bank. Such risks represent the credit facilities established for the bank's customers. These facilities are also referred to as risk-weighted assets (RWA), while the capital required is referred to as regulatory capital. The capital ratio resulting from the application of this formula may not be less than 8%. While Basel II does not change current the definition of regulatory capital, it modifies the definition of risk-weighted assets[99]. Theses changes include two main elements: a) substantive changes to the treatment of credit risk relative to the current accord, and b) the introduction of an explicit treatment of operational risk. The latter will result in a measure of operational risk being included in the denominator of the capital ratio.

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[98] see also Reich, O., Die Erweiterung der Marktdisziplin im Rahmen der Neuen Basler Eigenkapitalvereinbarung, 2003

[99] see paragraphs 240 to 253 of CP3 for a detailed definition

A major innovation of the new accord is the introduction of three options for the determination of credit risk and three options for the calculation of operational risk. The idea of providing for three options is to allow the banks a certain leeway to chose the approach which best serves their needs in terms of sophistication. Since this study focuses on credit risk, the options with regard to operational risk are not described in more detail. However, the three basic approaches for the calculation of credit risk shall be further discussed in this study.

5.3.1 Standardized Approach

The standardized approach represents the easiest approach. Banks are required to assign their credit exposures to supervisory categories based on observable characteristics of the exposure. Dependent on the classification, fixed risk weights are established. External credit assessments, i.e. external ratings of rating agencies are used. The risk weights are dependent on the type of claims. As an example, the risk weights for claims on corporates were proposed as follows:

Table 5.1: Risk weights for claims on corporates[100]

Credit Assessment	AAA to AA-	A+ to A-	BBB+ to BB-	Below BB-	Unrated
Risk Weights Corporates	20%	50%	100%	150%	100%

Past due loans are risk-weighted at 150%, unless a threshold amount of specific provisions has already been set side by the bank. Where no external rating is applied to an exposure, the standardised approach mandates a risk weight of 100%. With this, the Committee has taken into account the low ratings penetration outside the U.S.

Only 250 European companies are rated by S&P and Moody´s, while more than 2,000 companies and corporate bond issues are rated in the U.S. Assigning a risk weight of 150% to unrated exposure would penalize companies just because of limited ratings availability.[101] Another important feature is the expanded range of collateral, guarantees, and credit derivatives that banks which use the standardized approach may recognize.

5.3.2 Internal Ratings-Based Approaches (IRB)

The main difference between the IRB approaches and the standardized approach is that in the IRB approaches banks use their internal credit risk assessment systems to calculate the capital requirement. However, not all of the elements used for this calculation are determined by the banks. Instead, the risk weights and thus capital charges are computed by combining the quantitative input from the banks and formulas specified by the Basel Committee. These formulas translate the banks´ inputs into the capital requirement and are based on modern risk management techniques that involve a statistical assessment of risk.

The IRB calculation of RWA to corporate customers, banks, or sovereigns uses the same basic approach and relies on four quantitative inputs:

- Probability of default (PD): measuring the likelihood of a borrower's default
- Loss given default (LGD): representing the proportion of exposure that would be lost in case of default
- Exposure at default (EAD): representing the utilization of the facility at default

[100] De Nederlandsche Bank, Credit Risk - Standardised Approach, 2002, p. 9
[101] Cooper, L., The dawn of a new era, Risk Magazine, Oct. 1999

- Maturity (M): being the remaining economic maturity of the exposure

Table 5.2: Foundation versus Advanced IRB Approach[102]

Data Input	Foundation IRB	Advanced IRB
Probability of default (PD)	Provided by bank	Provided by bank
Loss given default (LGD)	Supervisory values set by the Committee	Provided by bank
Exposure at default (EAD)	Supervisory values set by the Committee	Provided by bank
Maturity	Supervisory values set by the Committee or At national discretion, provided by bank (with an allowance to exclude certain exposures)	Provided by bank (with an allowance to exclude certain exposures)

All IRB banks must provide internal estimates of PD. In addition, advanced IRB banks must provide internal estimates of LGD and EAD, while foundation IRB banks will make use of the supervisory values.

Whether a bank can opt for IRB Foundation or Advanced approaches is dependent on its supervisor's authorization and contingent on whether the bank can provide internal data verifying its calculations of probabilities of default (PD) or, in the case of the IRB Advanced Approach, all relevant variables (PD, LGD).[103]

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102 Basel Committee on Banking Supervision, Overview of the new Basel Capital Accord, 2003, p. 5

103 Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 5

5.4 Impact of Basel II on Banking

In order to find out what impact the implementation of Basel II may have on the banking industry, the Committee initiated three so-called "Quantitative Impact Studies". The third and most recent study - "Quantitative Impact Study 3" (QIS3) - was initiated in October 2002. Its results were published in May 2003.[104] The study involved more than 350 banks in 43 countries. The banks participating in this study were asked to quantify the impact of the proposed Basel II regulations on their business. Although there was concern about the quality and reliability of the results[105], the outcome of this study gives a first impression of potential implications.

On average, large banks[106] within the G10 countries would face an overall 10.5% increase of regulatory capital requirement compared to the requirements under the Basel I accord when the Standardized Approach is applied. The application of the Foundation IRB Approach would result in a 2.6% increase in required capital. However, applying the Advanced IRB approach would decrease the regulatory capital requirement by 1.6%. Smaller banks[107] would face an increase in regulatory capital requirement by 3.4% if they were to apply the Standardized Approach and would largely benefit from an application of the Foundation IRB Approach, which would result in a 19.4% decrease of required regulatory capital. A test of the Advanced IRB Approach was not performed, as this approach is not feasible for smaller banks due to its complexity.[108] Independent

[104] Basel Committee on Banking Supervision, Quantitative Impact Study 3 - Overview of Global Results, May 5, 2003
[105] Financial Times, "Bank Regulator Hits at Timetable for New Rules", June 17, 2003
[106] Large banks were defined as having capital in excess of EUR 3 billion, being diversified and internationally active.
[107] Smaller banks per definition were all banks which did not qualify as large bank.
[108] Basel Committee on Banking Supervision, Quantitative Impact Study 3 - Overview of Global Results, May 5, 2003, pp. 13

research by Salomon Smith Barney[109] came to a similar result, estimating that large, sophisticated banks would ultimately save 20% to 30% of regulatory capital.[110]

The QIS3 study reflects that, on average, the newly introduced capital charge for operational risk more than offsets any reduction in capital requirement resulting from the application of the IRB Approach. Although smaller banks seem to benefit substantially from the application of the IRB Approach, they often times lack the necessary resources to develop the required systems for the IRB Approach. Likely winners of Basel II would be banks specialized in SMEs and mortgages, whereas non-investment grade corporates and certain sovereigns would likely be losers.[111]

The consequences of the introduction of Basel II for the banking industry would certainly be substantial. Banks applying the Standardized Approach will face an increased requirement for capital. Most small banks will not be able to apply the IRB Approach due to a lack of resources. Larger banks are therefore facing an advantage over small banks, as larger banks are more likely to be able to implement the necessary methods and techniques for the application of the IRB Approach.

Banks specializing in asset management, custodial services, cash management, capital market activity, or similar services, will be among the losers of Basel II, as these institutions will be hit by the new capital charge for operational risk. Under the current accord, the aforementioned services do not require underlying capital. Banks specializing in retail lending will benefit, as it turns out that the retail

[109] Salomon Smith Barney is part of Citigroup. Citigroup is the largest financial group and is located in New York.
[110] The Banker, Can Basel II be made to work?, 2003
[111] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 9

portfolio is less risky than exposure to larger corporations. Consequently, less capital is required for the retail business.

Rating agencies will be among the winners of Basel II, as their role in sovereign and corporate lending will experience a major boost. Ratings assigned by these agencies are the base for the determination of the risk weight in the Standardized Approach.[112] An effect of Basel II may also be an acceleration of the global consolidation process in the banking industry, since the large banks as the winners will take advantage of their improved competitive position to take over smaller banks, which are among the losers of the New Capital Accord.[113]

5.5 Criticism on Basel II

Despite the fact that the Committee has pursued a policy of consultation, which has resulted in numerous changes of the proposed regulations, there are still areas of concern about the New Capital Accord. Harsh critics assert that the Committee has failed to address many of the key deficiencies of the global financial regulatory system and even created the potential for new sources of instability.[114] Although such criticism may be somewhat overstated, there is well-founded criticism on a number of issues.

5.5.1 Complexity

The final version of the Basel II regulations is expected to comprise approximately 1000 pages. It does not come by surprise, that such work is facing harsh criticism for being much too complex. Such

[112] Currently, only three internationally-recognised credit rating agencies exist: Standard & Poor´s, Moody´s and Fitch IBCA. See also Cooper, L., The dawn of a new era, Risk Magazine, Oct. 1999
[113] The Banker, Can Basel II be made to work?, 2003
[114] Danielsson, J., An Academic Response to Basel II, 2001

complexity may increase the risk of misinterpretation and unintended consequences[115], let alone the burden it represents on management time. Regulators reply that Basle II is necessarily complex because it addresses multiple risks in various areas of the banking industry.[116]

5.5.2 Costs

The application of Basel II will be costly and represent a significant burden, especially for smaller institutions. In many cases, the costs of implementing and maintaining the necessary systems will outweigh the benefits of lower capital charges. There are estimates, which put the cost of meeting the Basel II standards at $25 million to $50 million for a medium-sized bank.[117] But not only banks will face such expenses. Supervisors will take on additional responsibilities and will be confronted with substantially increased costs. Indirect costs will arise for other market participants as they have to adapt to the new disclosure requirements according to Pillar 3.[118]

Counter-arguments include that the costs of implementing Basel II are modest relative to the size of recent losses due to bad debt. This is evidence that there is need to improve risk management in banking and Basel II will support this improvement. Eventually, banks would have to incur such costs anyway, as they need to implement more sophisticated risk management systems.[119]

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[115] The Banker, Can Basel II be made to work?, 2003

[116] Global Risk Regulator, Risk-Based Regulation - a guide to the basics: Part 3, December 2002

[117] Global Risk Regulator, Risk-Based Regulation - a guide to the basics: Part 3, December 2002

[118] Reich, O., Die Erweiterung der Marktdisziplin im Rahmen der Neuen Basler Eigenkapitalvereinbarung, 2003

[119] Ferguson, R. W., Testimony before the Subcommittee on Domestic and International Monetary Policy, Trade, and Technlogy, committee on Financial Services, U.S. House of Repesentatives, February 27, 2003

5.5.3 Procyclicality

The linking of capital adequacy and credit ratings is problematic, as ratings use to be downgraded during economic down cycles. Bank will thus face increased capital requirements and will either have to raise capital or decrease their exposure, i.e. cut back on lending. As it is rather unlikely that banks will actually seek for additional capital to bolster their equity position in difficult times, the consequence may be a credit crunch and may have the potential for an adverse effect on the economy as to lengthen and deepen a recession.[120] The same would apply in the opposite direction with a booming economy.[121] In the worst case, such procyclicality could even trigger the collapse of certain European banking systems.[122]

Catarineu-Rabell, Jackson and Tsomocos (2003)[123] suggest therefore the application of rating schemes that are designed to be more stable over the economic cycle, similar to those of the external rating agencies. Public rating agencies factor cyclicality into their ratings in order to keep the ratings stable.[124]

5.5.4 Operational Charge

One of the most controversial topics of the new accord is the introduction of a capital charge for operational risk. There is disagreement as to wether the issue of operational risk is appropriately addressed through Pillar 1 or if it would be better to have it addressed by Pillar 2. Operational risk is mainly driven by the quality of the control environment of a bank and is therefore better

[120] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 15
[121] Global Risk Regulator, Risk-Based Regulation - a guide to the basics: Part 3, December 2002
[122] Economist, Judging the effects of new rules on bank capital, May 8, 2003
[123] Catarineu-Rabell, E., Jackson, P., Tsomocos, D., Procyclicality and the new Basel Accord - banks´choice of loan rating system, 2003

dealt with effective corporate governance, adequate internal structures, audit, compliance other qualitative tools as well as with insurance.[125] A capital charge won't be enough to cover the size of losses from low frequency but high impact events, such as rogue trading, that can eventually end up in the bankruptcy of the bank.[126] An example for a bankruptcy of a bank due to the failure of operational risk management is the demise of Barings Bank in 1995, which collapsed due to unauthorized trading activities of a single individual.[127]

Operational risk is furthermore difficult to evaluate and quantify. The procedure to develop the size of that charge is known as the advanced measurement approach (AMA). According to the AMA approach, banks calculate the operational risk on their own, adhering to certain broad guidelines. The supervisory authority is required to examine this calculation and make sure that it is comprehensive, systematic, and consistent with the guidelines.[128] Naturally, institutions particularly hard hit by the operational risk charge are the most harsh opponents of it. A number of U.S. banks that are specialized in businesses such as custody, asset management and payments systems have formed the "Financial Guardian Group" (FGG) to lobby on their behalf.[129]

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124 Standard & Poor´s, Corporate Ratings Criteria, 2003, p. 41

125 European Shadow Financial Regulatory Committee, Bank Supervisor`s Business: Risk Management or Systematic Stability?, Statement No. 16, May 12, 2003, p. 2

126 Global Risk Regulator, Risk-Based Regulation - a guide to the basics: Part 3, December 2002

127 Egger, C., Zur, M., Olofsson, C., Fallstudie: Barings Bank, Operational Risk Management, 2000

128 Ferguson, R. W., Testimony before the Subcommittee on Domestic and International Monetary Policy, Trade, and Technlogy, committee on Financial Services, U.S. House of Repesentatives, February 27, 2003

5.5.5 Disclosure Requirements

Although there is broad support for a mandatory disclosure for risk sensitive information, addressed through Pillar 3, the current proposal in the Third Consultative Document puts too much emphasis on quantitative information, rather than on qualitative disclosure.[130]

5.5.6 Level Playing Field Issues

The Basel II regulatory framework only applies to banks. Financial institutions may therefore have an incentive to operate such kind of business, to which a capital charge according to Basel II applies, in a separate entity, which is not considered a bank under Basel II. In particular, this may be the case in countries like the U.S., where non-bank competitors such as investment banks and insurance companies represent a large part of the financial system.[131] Large U.S. financial institutions that would currently not be covered by Basel II rules, as they are not registered as bank, include Goldman Sachs and Merril Lynch.[132]

5.5.7 Only Big Banks Will Benefit

Critics argue that Basel II is only to the benefit of large banks, as smaller institutions may not have the necessary means to set up the appropriate systems for Basel II. Smaller banks may not be able to keep up and may be swallowed by their larger competitors.[133] Basel

[129] The Banker, Can Basel II be made to work?, 2003
[130] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 16
[131] Credit Suisse Economic & Policy Consulting, Basel II: Implications for Banks and Banking Markets, 2003, p. 17
[132] The Banker, Can Basel II be made to work?, 2003
[133] Global Risk Regulator, Risk-Based Regulation - a guide to the basics: Part 3, December 2002

II may therefore trigger a wave of takeovers in the bank industry and thus accelerate the consolidation process. The large financial institutions will even be supported in their acquisition policy, as Basel II will reduce their capital requirement and thus free up capital which can be used to acquire the losers of Basel II.[134]

5.5.8 Negative Effect on Developing Countries

There is concern that linking ratings to capital requirement would have undesirable effects for developing countries. First, public ratings of banks and corporations in developing countries are rather uncommon. Consequently, banks in such countries will face high capital requirements. Second, corporate ratings in developing countries are strongly dependent on the sovereign rating of the country. Given the change in risk weights for sovereign exposure, corporations in developing countries may be hit twice.[135]

5.5.9 Banking Supervisors Become Too Powerful

Supervisors will play a key role under Basel II. There is concern that supervisors may use their power as an instrument of macro-economic policy.[136]

5.5.10 Basel II Increases Systematic Risk

Another worry is that the IRB approach will result in much greater homogeneity among bank's risk models. This will create new systematic risk. A systematic error in credit risk measurement could have a major effect on the financial system.[137]

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[134] The Banker, Can Basel II be made to work?, 2003
[135] Ferri, G., How the Proposed Basel Guidelines on Rating-Agency Assessments would affect developing countries, 2000
[136] Economist, Judging the effects of new rules on bank capital, May 8, 2003
[137] The Banker, Can Basel II be made to work?, 2003

5.6 Timeline and Outlook

According to the current time schedule, Basel II is intended to become effective end of 2006. The process of implementing the new capital accord into EU law and national law will begin upon publication of the final version of Basel II, which is scheduled for year-end 2003. The time schedule has been changed several times since the start of the consultation process and another deferral is not unlikely at this time.[138]

Upon implementation, the New Accord will have a lasting effect on the financial industry as a whole and on financial institutions in particular, regardless if they actually participate or not.

[138] In an interview with Reuters on October 11, 2003, Jaime Caruana, Chairman of the Basel Committee, has indicated that there may be a delay in the presentation of the final draft, which would, however, not cause a delay of the final implementation.

Chapter 6

Methodology

The ultimate goal of this dissertation is the creation of a credit risk model for the prediction of default of software companies. For this purpose, the following selections were made with regard to the selection of input variables, time horizon, methodology and accuracy measurement.

6.1 Input Variables

According to the literature and as described in previous chapters, financial ratios are useful variables for default prediction. Likewise, literature supports the use of qualitative information for default prediction purposes.[139] This study uses both financial ratios and qualitative information as variables for the credit risk model.

The data used in this dissertation encompassed quantitative and qualitative information on Austrian software companies and was provided by a major Austrian commercial bank. For industry classification purposes, the NACE classification was followed.[140] The focus on companies of <u>one</u> industry in <u>one</u> country (same regulatory environment) and <u>one</u> set of accounting standards is the only way to

[139] Blochwitz, S., Eigermann, J., Unternehmensbeurteilung durch Diskriminanzanalyse mit qualitativen Merkmalen, Zeitschrift für betriebswirtschaftliche Forschung, 52, pp. 58-73
[140] See chapter "Quantitative Model" for a detailed description of data.

ensure direct comparability of the results. Mixing companies from different industries or countries, or which apply different accounting standards, must necessarily negatively affect the quality of the results.

6.2 Time Horizon

A one-year time horizon for the default prediction in the credit risk model was chosen. The one-year horizon is in line with the current standard for credit risk models as they are currently used in banks (1999a)[141]. Banks use a one-year period as they normally review each credit facility once a year in order to reassess the financial condition of the company as well as the outlook for this obligor. The review is done for the purpose of reassessing the risk profile of the borrower and to re-evaluate the credit risk implied in the bank's credit exposure to the company. Typically, a review is done upon delivery of annual financial statements of the borrower to the bank. The review process is substantially identical with the standard credit analysis that is performed when the bank considers entry into a new credit exposure[142].

The main difference between a credit review and an analysis of a new transaction is that in a review the bank does not make a decision of either granting or not granting the loan, but rather of deciding whether a change in the exposure strategy towards this customer is necessary. Such change in exposure strategy may be a reduction in exposure, a request for additional security (collateral, guaranty etc.), or an exit of the exposure. In case the risk profile of the borrower has deteriorated, the bank will also try to enhance the

[141] Basel Committee on Banking Supervision, Credit Risk Modelling, Current Practises and Applications, Bank for International Settlements, 1999
[142] see chapter … credit analysis

pricing on the credit facility in order to ensure a balanced risk/return relation.

From the borrower's perspective, the one-year time period can be used to take certain measures aimed at improving its risk profile. Such measures may include the issue of new equity capital, a change in its business model towards lower business risk, a change in its information policy towards the lender, etc.

6.3 Model Selection

From the variety of different credit risk models as described in Chapter 4, the author choose to use a logistic regression for the creation of this credit risk model. The other models were excluded for the following reasons: Human expert systems do not seem to be state-of-the-art anymore and are too subjective. Market price-based models like KMV were not feasible for this study as no market price data is available for the companies used for this study. The linear discriminant analysis was excluded since it is regarded less advanced than the logistic regression. Finally, there is disagreement in the literature on the performance of models based on neural networks[143], which disqualified the neural network methodology from this study.

In the modeling process, financial ratios and qualitative factors were used as independent variables to predict default as the dependent variable. A stepwise selection process was performed.

[143] Caouette, J. B., Altman, E., Narayanan, P., Managing Credit Risk: The next great financial challenge, 1998, pp. 128-133, versus Boonyanunta, N., Zeephongsekul, P., State of the Art Credit Risk Analysis Model: Comparative Analysis between Statistical Approaches and Neural Network Approaches, 2000

6.4 Accuracy Measurement

The modeling process substantially aimed at creating a model with the strongest predictive power. The predictive power was measured with the concept of Cumulative Accuracy Profile (CAP).[144]

[144] See chapter 7.4 for a further description of the CAP concept.

Chapter 7

Quantitative Model

7.1 Description of Data

This study focuses on software companies. For definition and classification purposes, the study applies the OeNACE classification, which is the Austrian version of the NACE classification. NACE stands for "nomenclature générale des activités economiques dans les communautés européennes". The NACE classification is a standard for the classification of economic activities and is used by the European Union. Accordingly, this study analyzes companies that are assigned to one of the following NACE classes:

722001	Production of standard software
722002	Production of individual software
723000	Data processing
726000	Other activities related to data processing

The data analyzed was provided by a major Austrian commercial bank. Due to the Austrian Banking Secrecy Act, the identity of the companies was not disclosed by the bank and is therefore not known to the author of this study. The data set comprised 117 companies, whereby comprehensive financial statement data as well as qualitative information[145] was provided for each company. The data covered the time span from 1996 to 2001. Of these 117 companies, 5 companies had defaulted, i.e. the bank recognized a loan loss. The number of companies used for this study is in line with the sample size for similar analyses, e.g. Beaver[146] (79 companies), Altman[147] (66 companies), and, more recently, Chijoriga[148] (56 companies).

The breakdown of companies by NACE code was disclosed by the providing bank and is as follows:

Table 7.1: Breakdown of Sample by NACE Classification

NACE classification	**No of companies in sample**
Production of standard software	9
Production of individual software	45
Data processing	44
Other activities related to data processing	19
Total	**117**

Substantially all of the companies had prepared their financial statements according to the Austrian "Handelsgesetzbuch" (HGB), this way enabling consistency and comparability of the results of the analysis.

Not all the data provided was actually used in the analysis. The selection criteria for the financial statements were as follows:

Defaulted companies: Selected were the financial statements for the two fiscal years prior to the year in which the default occurred. In

[145] see chapter 7.1

[146] Beaver, W. H., *Financial Ratios as Predictors of Failure*, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111, 1966

[147] Altman, E., *Financial Ratios, Discriminant Analysis and Prediction of Corporate Bankruptcy*, Journal of Finance, Vol. XXIII, No. 4, pp 589-609, 1968

case the financial and qualitative information on the fiscal year prior to default was not available, the financial statements of the fiscal year two and three years prior to default were selected. Selected financial statements range from 1998 to 2001.

Non-defaulted companies: In order to allow comparability, a portfolio with similar distribution with fiscal years ranging from 1998 to 2001 was modeled.

7.2 Definition of Financial Ratios

Actual input for the creation of the quantitative model were the results of financial ratios, which were applied to the data set. For this purpose, financial ratios were selected and defined. The selection and definition of financial ratios was driven by the intention to examine those areas of a company which were deemed significant from a credit perspective.[149] The following areas were considered to be credit sensitive: Profitability, Capital Structure, Liquidity, Debt Service Coverage Growth, Productivity, Activity, Asset Quality, and Size. Additionally, the study captured specifics of the software industry and provided for such specifics by adjusting the definition of ratios accordingly.

7.2.1 Profitability

Profitability is a company's ability to generate earnings. Earnings and earning power refer to the recurring ability to generate cash from operations in the future and are some of the most important and reliable indicators of financial strength available. Earnings are

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[148] Chijoriga, M. M., *An application of credit scoring and financial distress, Prediction models to commercial bank lending: The case of Tanzania*, 1997
[149] see also Hayden, E., *Modeling an Accounting-Based Rating System for Austrian Firms*, 2002

reliable sources of cash for the longer-term payment of interest and repayment of principal. A stable trend of earnings is one of the best assurances of an enterprise's ability to borrow in times of cash shortage and its consequent ability to extricate itself from the very conditions that lead to insolvency[150]. A company that generates higher operating margins and returns on capital has a greater ability to generate equity capital internally, attract capital externally, and withstand business adversity. Earnings power ultimately attests to the value of the firm's assets as well.[151]

Profitability can be expressed in a variety of accounting ratios and is usually measured as profit relative to assets or profit relative to sales. Additionally, there is a variety of profit measures used, which most commonly include EBIT, pre-tax profit and net income. There are also different ways to define assets. With profitability ratios, there is always a positive relationship between profitability and creditworthiness.

Ratio P1: Return On Assets 1: EBIT

$$\frac{EBIT}{Average\ Total\ Assets}$$

Return on Assets measures how well the company utilizes its asset base to create profits by comparing profits with the assets that generate these profits.[152] EBIT stands for "Earnings Before Interest and Taxes" and is widely used as an accurate measure of profit from ordinary activities. Per definition, interest income/expense and any extraordinary income/expense is not taken into account. EBIT is therefore considered to represent the sustainable result from operations. By applying EBIT as the measure for earnings, the firm's

[150] Bernstein, L., *Financial statement analysis*, pp. 597-598, 1993
[151] Standard & Poor´s, *Corporate Ratings Criteria*, 2003
[152] Gibson, C., *Financial statement analysis*, pp. 379-385, 1994

profitability can be measured independent from the company's specific capital structure.

In theory, the actual average total assets would be based on daily figures. However, this information is not available to the outside analyst. For practical purposes, it is common practise to compute an average based on beginning and ending figures to arrive at an approximation. Of course, such approximation does not consider the timing of interim changes in assets and would not be appropriate for seasonal industries. Given the moderate cyclicality of the software industry, the author considers this approximation as acceptable.

<u>Ratio P2: Return On Assets 2: Net Income</u>

$$\frac{Net\ Income}{Average\ Total\ Assets}$$

In contrast to P1, ratio P2 takes interest expense/income, taxes, as well as extraordinary income/expense into account. It was computed in order to capture extraordinary costs from restructuring or write-offs that were frequently recorded by companies analyzed in this study.

<u>Ratio P3: Return On Assets 3: EBITDA</u>

$$\frac{EBITDA}{Average\ Total\ Assets}$$

Although actually a cash flow measure, EBITDA is becoming increasingly popular as a quasi-profitability measure, especially for high-tech and software companies.

<u>Ratio P4: EBIT Margin</u>

$$\frac{EBIT}{Net\ Sales}$$

Whereas the relationship of profit to assets measures how effectively assets are utilized, the relationship of profit (i.e. EBIT, EBITDA, net income) to sales measures operating performance.

Ratio P5: Net Income Margin

$$\frac{Net\ Income}{Net\ Sales}$$

Similar to P4, however this time using net income as the profitability measure.

Ratio P6: EBITDA Margin

$$\frac{EBITDA}{Net\ Sales}$$

Similar to P4, whereby EBITDA as a quasi-profit is used.

7.2.2 Capital Structure

The capital structure of a company is composed of equity and debt. The inherent financial stability of an enterprise and the risk of insolvency to which it is exposed are dependent on the sources of its funds.[153] Capital structure ratios are measures of the relative magnitude of the various sources of funds of the company and therefore for the extent of leverage (i.e. debt) used by the company to finance its operations.

Literature discusses a variety of capital structure ratios. Variations include the adjustment of assets and equity in the following ways:

[153] Bernstein, L., *Financial statement analysis,* p. 598, 1993

- Netting of cash and cash equivalents with debt, which was done for the following reasons:
  a) The company could use its cash to pay down debt. The actual net indebtedness is therefore lower. In contrast to the U.S., it is common practise in Europe to maintain a high level of debt while also maintaining a large cash position.[154]
  b) A company could have tried to improve its reported liquidity by raising short-term debt and reporting the drawn amount as available cash.
  c) A company could have borrowed money to invest it in short-term securities.[155]
- Deduction of intangible assets from assets and equity, as the value of such assets in case of liquidation is usually much lower than the book value.

Above adjustments were also proposed by Khandani/Lozano/ Carty[156], and Baetge/Jerschensky[157], respectively.

Ratio C1: Equity Ratio1

$$\frac{Equity}{Total\ Assets}$$

Subject ratio is most commonly used and a simple approach to examine the capital structure of a company.

Ratio C2: Equity Ratio 2

$$\frac{Equity + Subordinated\ Debt}{Total\ Assets}$$

[154] Standard & Poor´s, *Corporate Ratings Criteria*, 2003
[155] Brealey, R., Myers, S., Principles of Corporate Finance, p. 770, 1996
[156] Khandini, B., M. Lozano, and L. Carty, *Moodys RiskCalc for Private Companies: The German Model, Moody´s Investors Service*, 2001

This ratio considers subordinated debt as a form of quasi-equity. Subordinated debt is characterized by having a lower priority than that of another debt claim on the same assets or property. In case of bankruptcy, repayment of subordinated debt can not be claimed until all senior debt claims are satisfied. Sub-debt therefore becomes quasi-equity of the company. The significance of subordinated debt in a leverage ratio for this analysis is that such debt is widely used to finance start-up companies, especially in the software industry.[158]

Ratio C3: Equity Ratio 3

$$\frac{Equity - Goodwill}{Total\ \ Assets - Goodwill}$$

Acknowledging that certain kinds of intangible assets have a market value (e.g. licenses) and hence can be sold in the course of the liquidation of a company, this ratio only subtracts Goodwill from Assets and Equity. Application in the software industry: A software company has purchased a license to sell software, which was produced by a different software company. Such licenses may be transferable and therefore have a market value.

Ratio C4: Equity Ratio 4

$$\frac{Equity + Subordinated\ \ Debt - Goodwill}{Total\ \ Assets - Goodwill}$$

Ratio C5: Equity Ratio 5

$$\frac{Equity - In\tan gible\ \ Assets}{Total\ \ Assets - In\tan gible\ \ Assets}$$

[157] Beatge, J., and Jerschensky, A., *Beurteilung der wirtschaftlichen Lage von Unternehmen mit Hilfe von modernen Verfahren der Jahresabschlussanalyse*, in *Der Betrieb*, pp. 1581-1592, 1996

Ratio C6: Equity Ratio 6

$$\frac{Equity + Subordinated\ Debt - Intangible\ Assets}{Total\ Assets - Intangible\ Assets}$$

Ratio C7: Structure Ratio 1

$$\frac{Total\ Debt}{Total\ Assets}$$

The ratios C7 and C8 measure the amount of debt in relation to the size of the firm.

Ratio C8: Structure Ratio 2

$$\frac{Total\ Debt - Cash}{Total\ Assets - Cash}$$

Ratio C9: Leverage 1

$$\frac{Total\ Debt}{Total\ Debt + Equity}$$

Leverage ratios indicate the amount of funds provided by outsiders in relation to those provided by owners of the firm. It is therefore a different approach than comparing debt to assets. If a high proportion of the resources has been provided by outsiders, the risks of the business have been substantially shifted to the outsiders. A large proportion of debt in the capital structure increased the risk of not meeting the principal or interest obligation, because the company may not generate adequate funds to meet them.[159] Ratio C9 is

[158] see Hackl, E., *Flexibel finanzieren mit Mezzaninekapital*, in *IKB aktuell*,volume 136, 2003
[159] Gibson, C., *Financial Statement Analysis*, p. 311, 1994

considered the most comprehensive ratio in the area of capital structure.[160]

Ratio C10: Leverage 2

$$\frac{Total\ Debt - Cash}{Total\ Debt - Cash + Equity}$$

Ratio C11: Leverage 3

$$\frac{Senior\ Debt}{Total\ Debt + Equity}$$

Senior debt, as opposed to subordinated or junior debt, is debt which has priority for repayment in a liquidation. This ratio follows the distinction between these two types of debt and the consideration of subordinated debt in various leverage ratios.

Ratio C12: Leverage 4

$$\frac{Senior\ Debt - Cash}{Total\ Debt - Cash + Equity}$$

Ratio C13: Leverage 5

$$\frac{Total\ Debt}{Total\ Assets - Total\ Debt}$$

Ratio C14: Leverage 6

$$\frac{Total\ Debt - Cash}{Total\ Assets - Total\ Debt - Cash}$$

No separate ratios for short-term and long term debt were applied, as most of the debt presented by the companies in this study was short

[160] Bernstein, L., *Financial statement analysis,* p. 615, 1993

term. The reason for the modest need for long term financing is that software companies´ assets are predominantly short term. Also, there is a general trend of companies relying increasingly on short-term borrowings.[161]

7.2.3 Liquidity

Liquidity is certainly a crucial aspect in financial management, as a company needs to be able to meet its financial obligations when and as the fall due. Per definition, illiquidity, i.e. insolvency, results in bankruptcy of the firm. Liquidity ratios are therefore common variables in credit analyses, whereby there is a positive relationship between liquidity and creditworthiness. The better the liquidity situation of the company, the lower the probability of default.

<u>Ratio L1: Current Ratio</u>

$$\frac{Current\ Assets}{Current\ Liabilities}$$

A frequently applied indicator for short-term debt repayment ability is the current catio, which is computed by dividing the current assets by the current liabilities. Basically, a company´s current assets should always exceed its current liabilities. However, a current catio of less than 1.0 does not necessarily mean that the firm is bankrupt, since the company may be able to either defer payments or raise additional liquidity by drawings under unutilized credit lines or by capital contributions from the shareholders.

In turn, a company can face insolvency even though its current ratio is 1.0 or higher, when current assets can not be converted into cash in due course. This is especially the case with inventory which,

[161] Standard & Poor´s, *Corporate Ratings Criteria*, 2003

although generally classified as current, may be in stock for more than a year.

Ratio L2: Quick Ratio

$$\frac{Cash \,\&\, Cash\ Equivalents\ (Other\ Securities) + Accounts\ receivable}{Current\ Liabilities}$$

This ratio is called the quick ratio[162], because it only includes assets which are quickly convertible into cash, i.e. accounts receivable. Since it is believed, that inventory is the component of current assets, which is the least liquid, it is omitted from the acid test ratio. The quick ratio thereby understates, rather than overstates the liquidity position of a company.

A less conservative way of computation of liquidity is to only exclude inventory from current assets[163]:

$$\frac{Current\ Assets - Inventory}{Current\ Liabilities}$$

For the purpose of this analysis, the more conservative version of the quick ratio was applied.

Ratio L3: Cash Ratio

The best indicator of a company´s short-run liquidity is the cash ratio, since a company´s holdings of cash and marketable securities are its most liquid assets[164]. This ratio relates cash and cash equivalents to current liabilities. It would be wrong to expect a company to have enough cash to cover current liabilities. However, if the solvency of a company is impaired, the firm must depend on cash for its liquidity.

[162] Hoermann, F., "*Getting the OOPS! Out of Spreadsheets*", in "Journal of Accountancy", 10/1999, pp. 79-83
[163] Gibson, C., *Financial Statement Analysis*, p. 275, 1994
[164] Brealey, R., Myers, S., Principles of Corporate Finance, p. 770, 1996

$$\frac{Cash + Cash\ Equivalents}{Current\ Liabilities}$$

Ratio L4: Fixed Assets Coverage

$$\frac{Fixed\ \ Assets}{Equity + Long\ Term\ Debt}$$

This ratio measures to what extent fixed assets are covered by equity and long term debt. While fixed assets would ideally be entirely covered by equity, they should at least be covered by the total of equity + long term debt. Companies in the software industry usually carry only a small amount of fixed assets on their balance sheet.

7.2.4 Debt Service Coverage

The debt service coverage measures a company´s liabilities relative to its cash flow. It basically indicates a firm´s long-term debt-paying ability from the income statement view.[165] Similarly, interest coverage measures interest expense relative to a company´s earnings before interest and taxes (EBIT).

Ratio D1: Interest Coverage

$$\frac{EBIT}{Interest\ Expense}$$

In general, a firm must have sufficient funds to meet its obligations, including liabilities related to debt. Consequently, the result of this ratio must be greater than 1.0. In the short run, a firm can often meet its interest obligations even when the interest coverage is less than 1.0, because some of the expenses, such as depreciation and

[165] Gibson, C., *Financial Statement Analysis*, p. 311, 1994

amortization are non-cash and the company may have enough cash flow to cover interest expense.[166]

Ratio D2: Debt Coverage 1

$$\frac{Total\ Debt}{EBITDA}$$

This ratio is commonly used in credit analysis. It reflects by how many times debt exceeds EBITDA.

Ratio D3: Debt Coverage 2

$$\frac{Total\ Debt - Cash}{EBITDA}$$

As applied to the calculation of capital structure ratios (C8) as well as proposed by Khandani/Lozano/Carty[167], in this ratio as well as in several of the following debt coverage ratios, cash was subtracted from debt.

Ratio D4: Debt Coverage 3

$$\frac{Total\ Debt}{P\ \&\ L\ Cash\ Flow}$$

This ratio intends to measure leverage based on a different cash flow definition. For this purpose, the following cash flow definition was created and named P&L cash flow:

Operating profit before tax
+ Depreciation/Amortization
+/- Change in long term provision (provision for severance payments, provision for pensions) .
P & L Cash Flow

[166] Gibson, C., *Financial Statement Analysis*, p. 314, 1994
[167] Khandini, B., Lozano, M., and Carty, L., *Moodys RiskCalc for Private Companies: The German Model, Moody´s Investors Service*, 2001

Ratio D5: Debt Coverage 4

$$\frac{Total\ Debt - Cash}{P\ \&\ L\ Cash\ Flow}$$

For companies, which are partly financed by subordinated debt, coverage of senior debt can be calculated separately. In case of a cash shortage, the debtor might not be able to service its entire debt, but might have sufficient cash to meet obligations due to holders of senior debt. This following measures are particularly interesting for the software industry, where subordinated debt is frequently used to finance companies.

Ratio D6: Debt Coverage 5

$$\frac{Senior\ Debt}{EBITDA}$$

Ratio D7: Debt Coverage 6

$$\frac{Senior\ Debt - Cash}{EBITDA}$$

Ratio D8: Debt Coverage 7

$$\frac{Senior\ Debt}{P\ \&\ L\ Cash\ Flow}$$

Ratio D9: Debt Coverage 8

$$\frac{Senior\ Debt - Cash}{P\ \&\ L\ Cash\ Flow}$$

7.2.5 Productivity

Generally speaking, productivity is the amount of output per unit of input (e.g. labor, equipment, capital etc.). Given the large number of possible input and output factors, there are many different ways of measuring productivity. While productive capital may be considered the major input factor in a production company, it is human capital in the service industry. Given software being part of the service industry, the majority of productivity ratios applied in this study include human capital as an input factor. A firm´s productivity is considered to have some bearing on its likelihood of default.[168]

Ratio PR1: Sales per Employee

$$\frac{Sales}{Average\ Number\ of\ Employees}$$

This ratio measures the level of sales a company is able to generate per employee. It is widely applied, not only in the software industry but also in the manufacturing industries.

Ratio PR2: EBIT per Employee

$$\frac{EBIT}{Average\ Number\ of\ Employees}$$

Ratio PR3: EBITDA per Employee

$$\frac{EBITDA}{Average\ Number\ of\ Employees}$$

Ratio PR4: Net Income per Employee

$$\frac{Net\ Income}{Average\ Number\ of\ Employees}$$

Ratio PR5: Personnel Expense per Employee

$$\frac{Personnel\ Expense}{Average\ Number\ of\ Employees}$$

Ratio PR6: Personnel Expense/Fixed Costs

$$\frac{Personnel\ Expense}{Fixed\ Costs}$$

This ratio measures the relation of personnel costs to total fixed costs. Given that the software industry is human resource intensive, personnel expense is a major component of fixed costs.

Ratio PR7: Fixed Costs per Employee

$$\frac{Fixed\ Costs}{Average\ Number\ of\ Employees}$$

The intention of this ratio is to measure how much fixed costs the company incurs per employee.

7.2.6 Activity

These are ratios are meant to measure the efficiency at which a company is utilizing its assets and managing its liabilities to generate revenue.

[168] Khandini, B., Lozano, M., and Carty, L., *Moodys RiskCalc for Private Companies: The*

Ratio A1: Total Asset Turnover

$$\frac{Sales}{Average\ Total\ Assets}$$

Total asset turnover reflects the efficiency with which the available capital is used.[169] The entire assets of the company are taken into account in the denominator of the formula. Similar ratios can be defined for fixed assets and current assets (ratios A2 and A3).

Ratio A2: Fixed Assets Turnover

$$\frac{Sales}{Average\ Fixed\ Assets}$$

Ratio A3: Current Assets Turnover

$$\frac{Sales}{Average\ Current\ Assets}$$

Ratio A4: Accounts Receivable Turnover Days

$$\frac{Average\ Accounts\ \mathrm{Re}ceivable}{Sales * 1.2}$$

This ratio relates the amount of the accounts receivable to the average sales on account, whereby sales are multiplied by 1.2 in order to take the Austrian Value Added Tax (20%) into consideration. This ratio indicates the length of time that the receivables have been outstanding at the end of the year. As mentioned earlier, the result can be misleading when sales are seasonal.

German Model, Moody´s Investors Service, 2001

[169] Coenenberg, A., *Jahresabschluss und Jahresabschlussanalyse*, 1994

The ratio is of special significance for the industry under survey as it appears that many companies in the software industry, especially start-ups, suffer from an insufficient A/R management.

Ratio A5: Accounts Payable Turnover Days

$$\frac{Average\ Accounts\ Payable}{Cost\ of\ Materials\ and\ Services}$$

Subject ratio relates the amount of accounts payable to the company´s cost of materials and services. Similar to the A/R turnover ratio, the A/P turnover ratio can be affected by seasonal fluctuations.

7.2.7 Asset Quality

The ratios in this category intend to shed light on the quality of assets. The following ratios relate certain types of assets which do not have a market value or are difficult to evaluate (e.g. goodwill), to either sales or total assets of the company. The basic assumption is that such special asset types are of minor quality as their market value usually significantly departs from their book value in case of liquidation of the company.

Ratio Q1: Intangibles/Total Assets

$$\frac{Intangible\ Assets}{Total\ Assets}$$

Ratio Q2: Sales/Intangibles

$$\frac{Sales}{Average\ Intangible\ Assets}$$

7.2.8 Growth

It is frequently observed that companies suffer a decline is sales and/or a deterioration in profitability prior to default. Generally, it is better for a company to grow than to shrink. However, the relationship of growth and default is complex, as growth can also increase the default probability if the firm does not cope with the challenges that strong growth poses. Challenges mainly include the financing of growth, as extensive growth usually cannot be financed out of profits. Growth therefore often results in additional indebtedness and the build-up of the risks associated with debt[170].

Ratio G1: Sales Growth

$$\frac{Sales}{\Pr ev.\ Period\ Sales}$$

Basis for this ratio were net sales of the companies.

Ratio G2: Fixed Cost Growth

$$\frac{Personnel\ Expense + General\ \&\ Ad\min\ Expense + Depr.\ \&\ Amort.}{\Pr ev.\ Period\ Personnel\ Expense + General\ \&\ Ad\min\ Expense + Depr.\ \&\ Amort.}$$

This ratio includes personnel expense in fixed costs, although such expense can to some extent also be variable. Given most of the observed income statements having been prepared according to the "Total Cost Format", which does not divide personnel expense into the fixed and the variable part[171], such expenses were considered

170 Khandani, B., Lozano, M., Carty, L., "MOODY'S RISKCALC FOR PRIVATE COMPANIES:
THE GERMAN MODEL", 2001

171 In contrast to the "Total Cost Format", the "Cost of Sales Format" separates the fixed portion of personnel expense from variable costs. While the variable portion is included in "Cost of Sales", the fixed portion is included in "Sales expense" and "Administrative expense", respectively.

fixed for the purpose of this study. Indeed, personnel costs in the software industry are to the most extent fixed.

Ratio G3: Personnel Expense Growth

$$\frac{Personnel\ Expense}{\Pr ev.\ Period\ Personnel\ Expense}$$

Ratio G4: Marketing and Sales Expenses Growth

$$\frac{Other\ Operating\ Expenses}{\Pr ev.\ Period\ Other\ Operating\ Expenses}$$

The idea of this ratio is to capture the development of marketing and sales expenses. According to Austrian HGB, such costs are generally accounted for in the P & L item "other operating expenses"[172]. The increase/decrease of marketing and sales expenses is especially interesting in the case of software companies, as these costs usually represent major cost components in the industry.

Given the fact that the P&L item does also include costs other than marketing and sales, such as general administrative expense, subject ratio is skewed and is to be considered an approach rather than a precise indicator for marketing and sales expense growth.

Ratio G5: Total Assets Growth

$$\frac{Total\ Assets}{\Pr ev.\ period\ Total\ Assets}$$

[172] Bertl, R., Deutsch, E., Hirschler, K., *Buchhaltungs- und Bilanzierungshandbuch*, p 257

Ratio G6: Fixed Assets Growth

$$\frac{Fixed\ Assets}{\Pr ev.\ period\ Fixed\ Assets}$$

Ratio G7: Current Assets Growth

$$\frac{Current\ Assets}{\Pr ev.\ period\ Current\ Assets}$$

Ratio G8: Total Liabilities Growth

$$\frac{Total\ Liabilities}{\Pr ev.\ period\ Total\ Liabilities}$$

Ratio G9: Total Debt Growth

$$\frac{Total\ Debt}{\Pr ev.\ period\ Total\ Debt}$$

Ratio G10: Adjusted Total Debt Growth

$$\frac{Total\ Debt - Cash}{\Pr ev.\ period\ Total\ Debt - Cash}$$

In this ratio, total debt was adjusted by cash.

Ratio G11: Short Term Debt Growth

$$\frac{Short\ term\ Debt}{\Pr ev.\ period\ Short\ term\ Debt}$$

Ratio G12: Adjusted Short Term Debt Growth

$$\frac{Short\ term\ Debt - Cash}{\Pr ev.\ period\ Short\ term\ Debt - Cash}$$

Similar to ratio G10, short term debt was adjusted by cash.

7.2.9 Size

Sales or total assets are almost indistinguishable as reflections of size risk.[173] Smaller companies are usually less diversified, which makes them more exposed to cyclical downturns in specific industries. Furthermore, management is normally concentrated on a smaller number of people, increasing the key man risk[174]. Last but not least, as a general rule, the larger a company the more important its existence is for numerous stakeholders (vendors, customers, municipalities, government, etc.). Consequently, given their greater importance, larger firms will more likely be supported in times of distress, than smaller companies. Recent examples for such bail-outs include Philip Holzmann[175] and Alsthom[176].

Ratio S1: Sales

This is actually not a ratio, as the amount of sales was used.

Ratio S2: Total Assets

Similar to S1, the amount of total assets was used.

7.3 Explorative Analysis

Having applied the ratios as presented in Chapter 7.2 to the data - before starting creating the actual model - the author performed an explorative analysis. Aim of this analysis was to identify financial trends and locate areas in which defaulted companies are significantly different from non-defaulted companies. For this

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[173] Falkenstein, E., A. Boral, and L. Carty, *RiskCalc Private Model: Moodys Default Model for Private Firms, Moodys Investor Service,* 2000

[174] "Key man risk" is a commonly used term, referring to the risk, that one or a small number of people, on whose skills a company is highly dependent, leave the firm.

[175] Philip Holzmann, as one of the largest construction companies in Germany, was on the brink of bankruptcy in 1999, when it received political and financial support from the German Government.

purpose, mean and standard deviation were calculated for every ratio. This analysis follows Beaver´s approach in his examination of ratio analysis for failure prediction.[177] In this study, Beaver compared mean values of each of the ratios selected for his analysis and observed that there existed a high degree of consistence between ratios of failed and non-failed firms. One of his findings was that failed firms had lower cash flow ratios. Another finding was that failed companies had smaller liquid assets. Beaver also observed, that failed companys use more debt than non-failed firms.

To make sure that mean and standard deviation are not distorted by outlying values, such outliers[178] were eliminated beforehand. Outliers for the purpose of this research are defined as observations with values that are more than two standard deviations (+/-) away from the mean value. The study then covered approximately 95% of all observations. This approach allowed to eliminate excessively high values of the observed variable and as such controls for extra-ordinary outcomes.

Outlying results were typically caused by:

- companies with a low amount of sales and a highly positive or negative net income, causing outlying profit margins
- companies with strong cash flow and a small amount of debt, causing outlying debt service coverage ratios
- highly profitable companies with low indebtedness, causing outlying interest coverage ratios

[176] The large French engineering company experienced substantial financial support from the French Government, when it was close to collapse in July 2003.

[177] Beaver, W. H., Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111

[178] Acc. to "Statistics Glossary", http://www.cas.lancs.ac.uk/glossary_v1.1/presdata.html#out), an outlier is an observation in a data set which is far removed in value from the others in the data set. It is an unusually large or an unusually small value compared to the others.

Given the size of the data set, standard deviations in general remain high even after outliers were eliminated. Still, the mean values clearly indicate certain trends and evidence that conclusions can be drawn on the basis of the data set used for this study.

7.3.1 Profitability

Table 7.2: Mean Table for Profitability Ratios

In Percent		Non-Default		Default	
		Mean	SD	Mean	SD
P1	ROA 1: EBIT	7.04	24.84	-19.95	29.33
P2	ROA 2: Net Income	2.57	25.47	-17.51	29.14
P3	ROA 3: EBITDA	12.19	23.95	-14.00	27.16
P4	EBIT Margin	2.05	28.90	-23.62	28.22
P5	Net Income Margin	0.62	31.44	-20.34	28.75
P6	EBITDA Margin	3.02	37.98	-19.62	25.93

A clear trend is evidenced by the profitability ratios. On an EBIT basis, return on assets (P1) of non-defaulted companies is 7.04%, while the comparable mean value for defaulted companies is a negative 19.95%. Non-defaulted companies are also profitable on a net income basis (P2), while defaulted companies recorded a negative return on assets of 17.51% in the same period. The trend reflected by the return on assets ratio on EBITDA basis is consistent with the aforementioned findings. A positive 12.19% return for non-defaults compares to a negative 14.00% for defaults. The three margin ratios (P4 to P6) are in line with the ROA indicators and confirm the trend as reflected by ratios P1 to P3.

7.3.2 Capital Structure

Table 7.3: Mean Table for Capital Structure Ratios

In Percent		Non-Default		Default	
		Mean	SD	Mean	SD
C1	Equity Ratio 1	10.80	37.54	-20.54	28.07
C2	Equity Ratio 2	11.24	37.60	-20.54	28.07
C3	Equity Ratio 3	10.80	37.54	-20.54	28.07
C4	Equity Ratio 4	11.24	37.60	-20.54	28.07
C5	Equity Ratio 5	7.56	39.61	-21.07	28.25
C6	Equity Ratio 6	8.01	39.66	-21.07	28.25
C7	Structure Ratio 1	35.66	19.35	37.12	23.37
C8	Structure Ratio 2	33.71	19.64	35.85	23.29
C9	Leverage Ratio 1	67.02	116.27	249.90	382.01
C10	Leverage Ratio 2	73.03	91.45	246.05	388.27
C11	Leverage Ratio 3	74.60	91.38	249.90	382.01
C12	Leverage Ratio 4	73.03	91.45	246.05	388.27
C13	Leverage Ratio 5	64.10	71.17	67.29	62.52
C14	Leverage Ratio 6	62.52	75.78	66.22	74.72

The mean values of the equity ratios indicate significant differences in the equity position between non-defaulted companies and defaulted companies. While ratio C1 reflects a positive average equity position of 10.80% of assets for non-defaults, the comparable mean value for defaulted firms reflects negative equity of 20.54%. Taking subordinated debt as a substitute for equity into consideration (C2), the non-defaulted firm´s equity structure improves marginally to 11.24%. At the same time, there is no change on the end of the defaulted companies, signalling that none of these entities was financed by subordinated debt. C3 and C4 result in identical mean values as C1 and C2, reflecting that none of the companies analyzed in this study carries goodwill on its balance sheet. Similar to C1 to C4, non-defaulted companies also prevail in a tangible net worth (="TNW") consideration (C5 and C6). While at these companies TNW accounts for 7.56% (C5) and 8.01% (C6, including subordinated debt) of assets, defaulted companies had negative TNW of 21.07%.

C7 and C8 indicate that the percentage of debt to total assets is nearly the same in both segments. The picture changes when the equity position is taken into account. Leverage Ratio C9 shows a mean value of 67.02% for non-defaulted companies, while the comparable variable for defaulted companies is 249.90%. The main reason for the big difference is the average negative equity position of defaulted firms. Ratio C10 (debt net of cash), which is a measure similar to C9, confirms this trend. The leverage ratios C11 and C12, which measure leverage on a senior debt basis, also present much lower level of leverage for non-defaulted companies. Finally, ratios C13 and C14 confirm the findings of the previous variables.

Aforementioned observations are in line with the results of Beaver´s examination, who found that failed firms use more debt that non-failed companies[179].

7.3.3 Liquidity

Table 7.4: Mean Table for Liquidity Ratios

		Non-Default		Default	
		Mean	**SD**	**Mean**	**SD**
L1	Current Ratio	1.03	0.73	0.72	0.31
L2	Quick Ratio	0.69	0.53	0.35	0.28
L3	Cash Ratio	0.21	0.35	0.02	0.02
L4	Fixed Assets coverage	0.62	1.49	-0.19	0.53

With a mean value of 1.03, ratio L1 indicates that non-defaulted companies´ current assets marginally exceeded their current liabilities. For defaults, however, the average current ratio is well below 1, meaning that these companies carried a higher amount of current liabilities that they had in current assets. The Quick Ratio (L2) results in both cases in mean values below 1, whereby the respective mean of non-defaults indicates a better liquidity than the mean of defaulted firms. Ratio L3 presents that cash covers 21% of short-term liabilities. The same ratio for defaulted firms results in a mere 2%, evidencing a much weaker cash position. Non-defaulted companies also prevail in terms of fixed assets coverage (L4), where 62% of such assets are covered by either equity or long-term debt. At defaulted companies, the respective mean value is negative, which is mainly the result of negative average book equity at these companies (see capital structure ratios).

The results of the liquidity analysis are in line with the findings of Beaver, who observed that failed firms have smaller liquid assets.[180]

7.3.4 Debt Service Coverage

Table 7.5: Mean Table for Debt Service Coverage Ratios

		Non-Default		Default	
	Times	Mean	SD	Mean	SD
D1	Interest Coverage	7.40	9.29	negative	n/a
D2	Debt Coverage 1	2.03	1.62	negative	n/a
D3	Debt Coverage 2	1.93	1.65	negative	n/a
D4	Debt Coverage 3	2.51	1.96	negative	n/a
D5	Debt Coverage 4	2.37	1.99	negative	n/a
D6	Debt Coverage 5	1.99	1.62	negative	n/a
D7	Debt Coverage 6	1.90	1.66	negative	n/a
D8	Debt Coverage 7	2.47	1.97	negative	n/a
D9	Debt Coverage 8	2.33	2.00	negative	n/a

The mean value of interest coverage (D1) indicates that in case of non-defaulted companies EBIT was 7.4 times interest expense on average. Eight of the analyzed non-defaulted companies had a negative interest coverage. The same calculation for defaulted companies shows that the majority of these companies had negative interest coverage, while only two of the defaulted companies had

179 Beaver, W. H., Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111
180 Beaver, W. H., Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111

positive interest coverage. A calculation of mean value and standard deviation for defaulted companies is therefore not meaningful.

Ratios D2 to D9 measure to what extent debt (total debt and senior debt) is covered by cash flow (EBITDA or P&L cash flow). D2 results in a mean value of 2.03, reflecting that total debt was on average 2.03 times EBITDA in the case of non-defaulted firms. At 5 of these companies, total debt was in excess of EBITDA. At defaulted firms, subject calculation results in negative values for the majority of companies. The same picture is presented by D3, where debt was netted with cash. D4 and D5 are similar ratios, whereby P&L cash flow is used as the source of repayment. Non-defaulted companies have a mean value of 2.51 and 2.37, respectively, while at the majority of defaulted firms, P&L cash flow is negative. In general, the results suggest that P&L cash flow is stronger than EBITDA in this data set, as the mean values for ratios D2 und D3 are lower than the ones for D4 and D5.

Performing a similar analysis on the basis of senior debt instead of total debt, provides a picture with the same indication. While coverage of senior debt by EBITDA and P&L cash flow is on average around 2, the majority of defaulted firms had a negative debt coverage according to this survey.

The results of the debt service coverage analysis are consistent with the observations of Beaver, who found that failed firms have lower cash flow ratios.[181]

7.3.5 Productivity

Table 7.6: Mean Table for Productivity Ratios

in Tsd. EUR, except for PR6 (in %)		Non-Default		Default	
		Mean	SD	Mean	SD
PR1	Sales per Employee	181.49	174.48	84.82	5.41
PR2	EBIT per Employee	9.73	27.86	-17.15	30.72
PR3	EBITDA per Employee	18.86	40.20	-15.67	28.89
PR4	Net Income per Employee	3.75	22.69	-18.71	32.33
PR5	Person. Exp./Employee	46.55	25.13	34.27	37.14
PR6	Person. Exp./Fixed Costs	0.53	0.21	0.57	0.17
PR7	Fixed Costs per Employee	78.66	45.16	48.62	50.41

According to the mean value of PR1, sales productivity of non-defaulted companies was higher than that of defaulted companies. With sales of EUR 84.82 Tsd., an employee of a defaulted firm generated on average less than half of what was generated by an employee of a non-defaulted company. From a profitability perspective (PR2 to PR4), employees of non-defaulted firms also clearly prevail, as all profitability measures for defaulted firms are negative.

An analysis of the cost structure leads to the conclusion, that average personnel expense per employee (PR5) is higher in case of non-defaulted firms than it is in the segment of defaulted companies. While an average non-defaulted company expensed EUR 46.45 Tsd. per year, the defaulted entities spent only EUR 34.27 Tsd. per person. Personnel expense as a percentage of total fixed costs (PR6) is higher than in non-defaulted companies. In line with PR5, PR7 reflects that average fixed costs per employee in a defaulted company were lower than in a non-defaulted firm.

In general, the results may suggest that profitability is driven by sales productivity. Although an average non-defaulted company spent

[181] Beaver, W. H., Financial Ratios as Predictors of Failure, Empirical Research in Accounting, Supplement to Journal of Accounting Research, pp 71-111

more on employees and had to cover relatively higher total fixed costs, this was more than off-set by a significantly higher sales generation per employee.

7.3.6 Activity

Table 7.7: Mean Table for Activity Ratios

		Non-Default		Default	
	Times	**Mean**	**SD**	**Mean**	**SD**
A1	Total Asset Turnover Days	379.35	435.79	243.36	116.62
A2	Fixed Asset Turnover Days	86.01	152.01	33.23	36.40
A3	Current Asset Turn. Days	236.56	285.65	218.83	123.62
A4	A/R Turnover Days	63.89	51.11	79.22	16.70
A5	A/P Turnover Days	128.04	151.61	74.31	38.61

Ratios A1 to A3 measure asset turnover. A1 presents average turnover days of 379 for non-defaulted firms, which is significantly slower than the respective turnover at defaulted companies. This is mainly caused by much slower turnover of fixed assets (A2) at non-defaulted entities, which, with a mean value of 86 days, is much slower than at defaulted companies. From a current asset perspective (A3), the difference between the two segments is much smaller, whereby turnover at defaulted firms is again faster.

Ratio A4 measures the turnover pattern of accounts receivable. It shows that non-defaulted companies have a faster A/R turnover, as the average collection period is approximately 64 days. At the same time, it took a defaulted firm on average almost 80 days to turn accounts receivable into cash. A significant difference between the two segments is presented by ratio A5, calculating the accounts payable turnover. It seems that non-defaulted entities pay their A/P much later than defaulters. While the latter settle such obligations on average after 74 days, the former pay on average after 128 days.

7.3.7 Asset Quality

Table 7.8: Mean Table for Asset Quality Ratios

Q1: In Percent Q2: In Hundreds of Percent		Non-Default		Default	
		Mean	SD	Mean	SD
Q1	Intangibles/Total Assets	2.71	4.19	0.82	0.09
Q2	Sales/Intangibles	229.11	274.64	158.94	136.66

These ratios indicate that non-defaulted companies carried relatively more intangible assets than defaulted companies. While intangible assets accounted for 2.71% of total assets of non-defaulted companies, such assets presented less than 1 percent of total assets of defaulted entities. A similar picture is provided by analyzing the sales to intangibles relation.

7.3.8 Growth

Table 7.9: Mean Table for Growth Ratios

In Percent		Non-Default		Default	
		Mean	SD	Mean	SD
G1	Sales Growth	19.91	54.52	-7.93	50.18
G2	Fixed Cost Growth	18.38	41.16	22.29	13.94
G3	Personnel Exp. Growth	15.08	43.58	37.97	36.38
G4	Marketing Costs Growth	18.86	47.71	18.90	52.63
G5	Total Assets Growth	17.44	36.28	56.31	69.14
G6	Fixed Assets Growth	9.20	46.05	72.49	43.12
G7	Current Assets Growth	16.24	50.77	32.35	73.79
G8	Total Liabilities Growth	17.20	48.28	59.98	73.15
G9	Total Debt Growth	11.87	98.99	23.11	50.88
G10	Adj. Total Debt Growth	3.68	92.41	43.42	45.88
G11	Short Term Debt Growth	15.47	123.19	23.11	50.88
G12	Adj. Short Term Debt Growth	11.71	137.37	43.42	45.88

The mean value of sales growth (ratio G1) reflects that non-defaulted companies increased sales by almost 20%. In sharp contrast, companies, which later on defaulted, experienced a decline in sales by 7.93% on average. Fixed costs (G2) grew in both cases in substantially the same magnitude. Development of personnel expense (G3), however, varies significantly. While such expense grew by 15% at non-defaults, a strong 38% growth is reflected at defaulted companies. Marketing costs (G4), similar to total fixed costs, show the same picture in both segments.

A clear trend is indicated with regard to development of the balance sheet. While total assets (G5) of the companies under survey were in general growing, assets of defaulted companies grew by 56%, while the balance sheet of the non-defaults grew by only 17%. The difference is even bigger at fixed assets (G6). A 9.2% increase in case of non-defaults compares to a substantial 72.49% increase on the end of defaults. The difference in terms of current assets growth (G7) is not as big as is the case at fixed assets, however, the growth is stronger at defaulted firms. Ratio G8 indicates to what extent such asset growth was financed by additional liabilities. In both cases, growth in liabilities is in line with growth in assets. As a conclusion, growth was in general substantially financed through additional liabilities.

Ratios G9 to G12 measure the change in indebtedness of the companies. Three trends are recognizable: Firstly, defaulted companies were entirely short-term financed. Secondly, leverage of defaulted companies grew higher than leverage of non-defaulted companies. Thirdly, adjusted debt (cash netted with debt) of defaulted companies grew stronger than gross debt. This leads to the conclusion that the cash position of defaulted companies has deteriorated in the year of observation. In case of non-defaults, adjusted debt growth is weaker than growth of gross debt, indicating that their cash position has improved.

7.3.9 Size

Table 7.10: Mean Table for Size Ratios

In EUR 000´		Non-Default		Default	
		Mean	SD	Mean	SD
S1	Sales	8,063.11	23,362.48	2,979.66	4,382.08
S2	Total Assets	4,791.73	11,709.40	1,740.07	1,616.10

The mean values of the size ratios indicate that the average size of non-defaulted companies exceeds the size of defaulted firms both in terms of sales and total assets.

7.4 Measuring Predictive Power

The concept of the Cumulative Accuracy Profile was applied to each of the ratios as presented in chapter 6.2.

7.4.1 Profitability

Table 7.11: Predictive Power of Profitability Ratios

		AR
P1	Return on Assets 1: EBIT	50
P2	Return on Assets 2: Net Income	49
P3	Return on Assets 3: EBITDA	61
P4	EBIT Margin	52
P5	Net Income Margin	55
P6	EBITDA Margin	63

All Profitability ratios have a strong predictive power, with the EBITDA margin (P5) being the most predictive variable with a discriminatory power of 63%. P3 as the measure of Profitability based on EBITDA follows with a predictive power of 61%.

7.4.2 Capital Structure

Table 7.12: Predictive Power of Capital Structure Ratios

		AR
C1	Equity Ratio 1	60
C2	Equity Ratio 2	61
C3	Equity Ratio 3	60
C4	Equity Ratio 4	61
C5	Equity Ratio 5	56
C6	Equity Ratio 6	57
C7	Structure Ratio 1	-32
C8	Structure Ratio 2	-36
C9	Leverage 1	-3
C10	Leverage 2	-5
C11	Leverage 3	0
C12	Leverage 4	0
C13	Leverage 5	-32
C14	Leverage 6	-37

The capital structure ratios present a very inconsistent picture. While there are a number of variables with a highly postive predictive power (equity measures), an almost equal number of variables result in negative discriminatory power (C7, C8, C13, C14). Furthermore, four leverage ratios have a negligible or no predictive power at all (C9 to C13).

7.4.3 Liquidity

Table 7.13: Predictive Power of Liquidity Ratios

		AR
L1	Current Ratio	39
L2	Acid Test Ratio	43
L3	Cash Ratio	70
L4	Fixed Assets Coverage	59

The set of liquidity ratios contains two powerful predictors: the cash ratio (L3) with 70% and the fixed assets coverage (L4) ratio with a discriminatory power of 59%.

7.4.4 Debt Service Coverage

Table 7.14: Predictive Power of Debt Service Coverage Ratios

		AR
D1	Interest Coverage	43
D2	Debt Coverage 1	12
D3	Debt Coverage 2	-3
D4	Debt Coverage 3	8
D5	Debt Coverage 4	-4
D6	Debt Coverage 5	12
D7	Debt Coverage 6	-3
D8	Debt Coverage 7	-12
D9	Debt Coverage 8	-4

Only the interest coverage ratio turned out to have a strong predictive power. The remaining coverage ratios have a low discriminatory power.

7.4.5 Productivity

Table 7.15: Predictive Power of Productivity Ratios

		AR
PR1	Sales per Employee	57
PR2	EBIT per Employee	53
PR3	EBITDA per Employee	60
PR4	Net Income per Employee	49
PR5	Personnel Expense per Employee	31
PR6	Personnel Expense/Fixed Costs	0
PR7	Fixed Costs per Employee	-30

Several productivity measures indicate a strong predictive power. Only PR6, which tests the relation of personnel expense to fixed costs is useless for a rating model as the calculation results in a power of 0. Such ratio is therefore no better than a random variable.

7.4.6 Activity

Table 7.16: Predictive Power of Activity Ratios

		AR
A1	Total Asset Turnover Days	-10
A2	Fixed Asset Turnover Days	27
A3	Current Asset Turnover Days	-20
A4	Accounts Receiv. Turnover Days	39
A5	Accounts Payable Turnover Days	1

With A4 as the ratio for accounts receivable turnover, only one variable suggests a discriminatory power in excess of 30%. In general, the results are mixed.

7.4.7 Asset Quality

Table 7.17: Predictive Power of Asset Quality Ratios

		AR
Q1	Intangibles/Total Assets	56
Q2	Sales/Intangibles	-34

Q1 results in a strong discriminatory power of 56%. The predictive power of Q2 is a negative 34%, indicating that the lower the Sales/Intangibles relation, the higher the default frequency.

7.4.8 Growth

Table 7.18: Predictive Power of Growth Ratios

		AR
G1	Sales Growth	22
G2	Fixed Cost Growth	-26
G3	Personnel Expense Growth	-32
G4	Marketing Costs Growth	-6
G5	Total Assets Growth	-31
G6	Fixed Assets Growth	-62

G7	Current Assets Growth	-21
G8	Total Liabilities Growth	-36
G9	Total Debt Growth	-10
G10	Adjusted Total Debt Growth	-36
G11	Short Term Debt Growth	15
G12	Adjusted Short Term Debt Growth	-54

G6 as the ratio for Fixed Assets growth has the strongest predictive power in this set of variables. The power is a negative 62%, indicating that defaults occurred at companies with a comparably small growth in fixed assets. Strong predictive power was furthermore assigned to the ratio for adjusted short term debt growth.

7.4.9 Size

Table 7.19: Predictive Power of Size Ratios

		AR
S1	Sales	2
S2	Total Assets	-6

Both ratios for size have a very modest predictive power.

7.5 Selection of Variables

Having the ratios tested for their individual predictive power, the next step was to select the ones to be used for the modeling process. Reason for the focus on a smaller number of variables as opposed to using all variables for the modeling process was to avoid an "overfit" - a model which is overly geared towards the underlying data set and which therefore has few degrees of freedom. Although an overfit model would have a strong discriminatory power for the underlying data set, its general predictive power for a different data set would be weak.

Main selection criterion for the "shortlist" of variables was the individual predictive power of the variables. Additionally, the following criteria were taken into consideration and resulted in the selection or exclusion of certain variables from the longlist:

a) Coverage of all credit sensitive areas: It was intended to take all credit sensitive areas (capital structure, profitability etc.) into consideration, even though in some cases the predictive power of a variable selected under this criterion was weaker than certain non-selected variables. For example, the accounts receivable turnover ratio was included in the shortlist, although its predictive power of 39% is lower than the predictive power of certain non-selected variables from other areas. It would not be meaningful, to base a rating model solely on ratios from one area.

b) Correlation: If there were a strong correlation between two financial ratios, only one of these ratios was included in the shortlist. If both had been included, the same information would have been represented twice. In order to test for correlation among the variables, a correlation matrix was established. Subject matrix is attached to this study (see Appendix).

c) Data consistency: The growth ratios (G1 - G12) were not considered for the shortlist, as the reliability of the respective results was deemed inferior, given that for a number of companies the prior year of the financial year under review was not available.

Following the above rules, the following variables were selected for the shortlist:

Table 7.20: Shortlist of Quantitative Variables

		AR
P1	Return On Assets 1: EBIT	50
P3	Return On Assets 3: EBITDA	61
P4	EBIT Margin	52
P6	EBITDA Margin	63
C1	Equity Ratio 1	60
C2	Equity Ratio 2	61
C5	Equity Ratio 5	56
C6	Equity Ratio 6	57
L1	Current Ratio	39
L2	Acid Test Ratio	43
L4	Fixed Assets Coverage	59
D1	Interest Coverage	43
PR1	Sales per Employee	57
PR2	EBIT per Employee	53
PR3	EBITDA per Employee	60
A4	Accounts Receiv. Turnover Days	39

7.6 Standardizing Results

Before performing the actual logistic regression, the results of the variables from the shortlist were standardized. The standardization was aimed at making the results comparable in a way that they have the same mean and the same standard deviation. A further benefit of this standarization is that the coefficients which will later on be derived from the logistic regression can be interpreted as "weights" of the variables in the final rating model.

Furthermore, an "effective area" was chosen for each of the variables from the shortlist by determining an upper and a lower bound. The rationale for the determination of such effective area is that the incremental improvement of a company´s creditworthiness through an incremental improvement of a ratio varies. While a 5% improvement of a company´s equity ratio may be considered a significant improvement of its creditworthiness when such ratio was

2% before and is now 7%, it may not be considered a substantial improvement, if the company had already an equity ratio of 80%.

The upper bound is therefore meant to represent a value beyond which an improvement of the underlying ratio would not result in a significant improvement in a company´s creditworthiness. Similarly, the lower bound represents a value below which a deterioration of the underlying ratio would not significantly further deteriorate the creditworthiness.

The following upper and lower bounds were determined for the variables from the shortlist:

Table 7.21: Upper and Lower Bounds of Quantitative Variables

		Upper Bound	Lower Bound
P1	Return On Assets 1: EBIT	50%	- 70%
P3	Return On Assets 3: EBITDA	50%	- 70%
P4	EBIT Margin	50%	- 70%
P6	EBITDA Margin	50%	- 70%
C1	Equity Ratio 1	50%	- 85%
C2	Equity Ratio 2	50%	- 85%
C5	Equity Ratio 5	70%	- 85%
C6	Equity Ratio 6	70%	- 85%
L1	Current Ratio	3.00	0.10
L2	Acid Test Ratio	3.00	0.03
L4	Fixed Assets Coverage	3.00	-1.00
D1	Interest Coverage	20 times	- 5 times
PR1	Sales per Employee	EUR 300,000.00	EUR 1.00
PR2	EBIT per Employee	EUR 50,000.00	- EUR 60,000.00
PR3	EBITDA per Employee	EUR 70,000.00	- EUR 50,000.00
A4	A/R Turnover Days	0	150

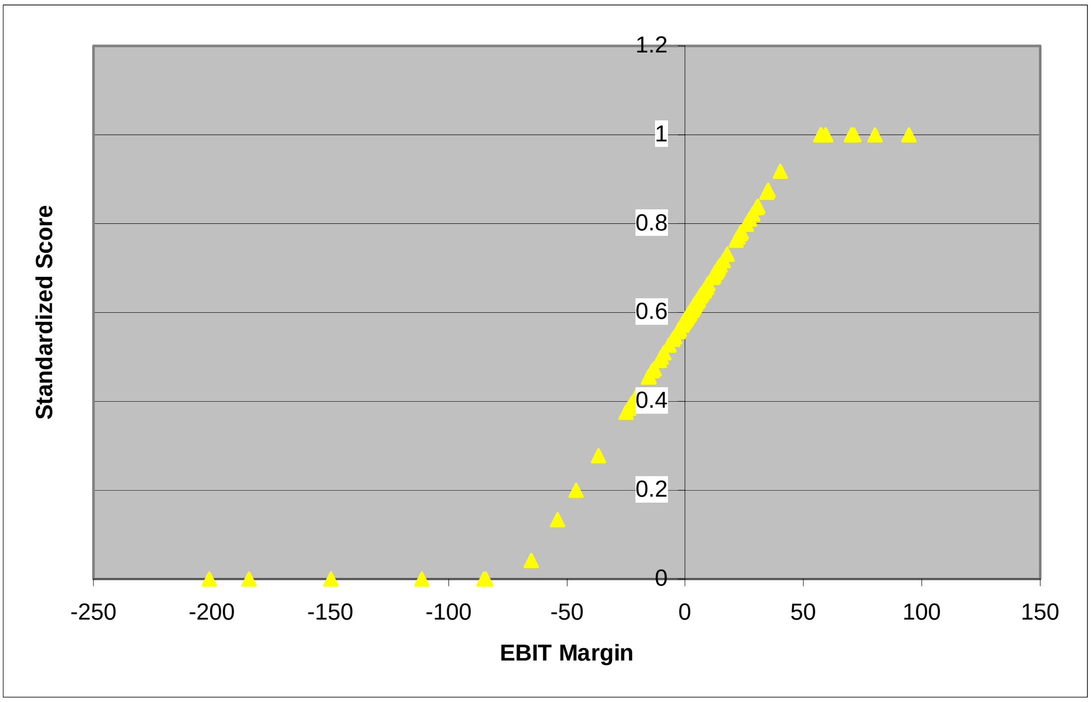
The "Corporate Ratings Criteria"[182] of Standard & Poor´s[183] (S & P) offered guidance for the determination of the upper bounds. Subject report includes ratio medians for companies, which were assigned a rating of AAA by S & P, representing the best possible rating for a company. AAA therefore reflects the strongest credit profile. For the

[182] Samson, S. et al, "Corporate Ratings Criteria", 2003

purpose of this study, it was assumed that the creditworthiness of a company cannot be improved any further, if the variable of the company has met the respective ratio median of the AAA companies. For example, the ratio median for interest coverage of the AAA companies is 21.4x.[184]

The following figure illustrates the standardization as well as upper and lower bounds for the EBIT margin variable.

Figure 7.1: Standardized EBIT Margin



7.7 Logistic Regression and Quantitative Model

A logistic regression was now performed with the standardized scores of the variables from the shortlist. For such regression, a stepwise approach was chosen and carried out with SPSS 11.0. Consequently, a model was built by adding variables or, respectively,

[183] Standard & Poor´s is a major credit rating agency and is located in New York, USA

excluding variables from the model. The F-probabilities as the bounds chosen for inclusion and exclusion of variables were 0.50 and 0.95, respectively.

It should be noted that this statistical stepwise selection process has been criticized and been considered as "data mining". However, as argued by Hesmer and Lemenshow[185], as well as Hendry and Doornik[186], such selection process is necessary when dealing with a large number of input factors. For example, with the roughly 20 variables from the shortlist of this study, more than 1 million possible models could be established. Therefore, even if a stepwise regression were "data mining", this approach would be more efficient than any trial-and-error strategies in finding powerful models.[187]

Having completed the stepwise selection process, SPSS depicted the following model:

Table 7.22: Initial Quantitative Model

Variable	**Coefficient**	**Significance**
Constant	-21.344	0.000
C2	-5.027	0.182
P4	-4.679	0.389
L4	-1.331	0.158
A4	-0.933	0.313
C6	3.815	0.334
L2	-0.861	0.538
D1	0.862	0.530
P6	2.875	0.586

The model comprises eight variables, each of them having different contributions to the model. As a rule, the higher the negative or positive value of the coefficient, the bigger is its weight in the model.

[184] Samson, S. et al, "Corporate Ratings Criteria", p 54, 2003
[185] Hosmer, D., Lemenshow, S., Applied Logistic Regression, 1989
[186] Hendry, D., Doornik, J., Modelling Linear Dynamic Econometric Systems, Scottish Journal of Political Economy, pp. 1-33
[187] Hayden, E., Modeling an Accounting-Based Rating System for Austrian Firms, p. 44, 2002

Three of the variables have positive signs, i.e. their contribution to the model is contrary to what was indicated by their predictive power. For example P5: Although the individual predictive power of this ratio is a strong 63%[188], its contribution to the model is positive. This would actually mean that the stronger the profitability of a company in terms of EBITDA margin, the more likely is its default. While this is true as far as its contribution to the model is concerned, such conclusion is in general not meaningful. Having ambiguous conclusions in a rating model makes it difficult to comprehend and interpret the results. Therefore, for the sake of making the rating system plausible and reasonably comprehensible for practical users, variables with positive signs were excluded from the model.

Additionally, the author attempted to expand the set of included ratios into ratio categories which have not been selected by SPSS. Consequently, various models with different compositions in terms of ratios were created and tested for their rating accuracy. Given the big number of interim models created and tested, the presentation of all models in this study would not be meaningful. Therefore, only the final model is presented. It includes the following ratios and weights:

Table 7.23: Final Quantitative Model

Variable	**Coefficient**	**Significance**
Constant	-21.002	0.000
C2	- 1.814	0.045
P4	- 1.205	0.183
PR1	-0.604	0.605
A4	- 0.887	0.304

The model consists of four variables from four different ratio categories. In each case, the contribution is negative. The weights are different. The different contribution is also reflected by different values for significance. The variable with the strongest contribution

188 see Chapter 6.4

is C2, measuring equity plus subordinated debt as a percentage of total assets. The related significance of this ratio is 0.045. Second highest weight has P4, a profitability ratio measuring the EBIT margin. The respective significance is 0.183. The final rating model also captures productivity, represented by PR1. This ratio measures the productivity of companies in terms of sales per employee and reflects a significance of 0.605. The model finally also includes an activity measure, with A4 indicating the borrower´s activity as far as accounts receivable management is concerned.

Therefore, the quantitative models suggests that the probability of default of a company decreases

- the higher the ratio of its equity plus subordinated debt is to its total assets
- the stronger its profitability in terms of EBIT margin
- the more productive it is as measured by sales per employee
- the faster its accounts receivable turnover is

The final model was applied to the data set at hand and tested for rating accuracy. The result is an AR of 67.5%. Comparing this AR with similar studies, as for example Falkenstein/Boral/Carty[189] or Hayden[190] leads to the conclusion that the predictive power of 67.5% is in line with the discriminatory power of similar rating models.

[189] Falkenstein, E., A. Boral, and L. Carty, *RiskCalc Private Model: Moodys Default Model for Private Firms*, Moodys Investor Service, 2000

[190] Hayden, E., *Modeling an Accounting-Based Rating System for Austrian Firms*, 2002

Chapter 8

Qualitative Model

8.1 Description of Qualitative Data

The qualitative data was provided by a major Austrian commercial bank, the same bank that had provided the quantitative data used in this study[191]. The qualitative data represents the answers on a questionnaire, which was filled out by employees of the bank. These employees were the account officers of the companies which were included in the study at hand. The account officers had to evaluate different aspects of their customers and appraise them according to a predefined grading scale. Therefore, these appraisals are subjective by nature.

The questionnaire covered six areas of a company, whereby several questions were to be answered for each area. Depending on what the questions were directed at, the answer had to be given either in the form of a grading, ranging from 1 to 5 (1 being the highest rating and 5 being the lowest rating), or in the form of a simple "Yes", "No" or "Not known". The selection "Not known" was generally assigned to the lowest grading category. The form of the questionnaire represents the standard questionnaire used by this bank for rating purposes[192] and was designed as follows:

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[191] see chapter 6.1
[192] Unternehmensfinanzierung im Wandel. Der Weg vom Kreditmarkt zum Kapitalmarkt. Bank Austria Creditanstalt AG, 2002

	Management	Grading
QF1	Existence of a long-term business concept, which clearly defines goals and strategy?	Yes/No/Not known
QF2	Industry-specific expertise of the management?	1 to 5, Not known
QF3	Leadership style with regard to the ability to decide, delegate and motivate?	1 to 5, Not known
QF4	Defined management succession?	Yes/No/Not known
QF5	Information policy towards the bank?	1 to 5, Not known

	Accounting	Grading
QF6	Quality of accounting and reporting instruments?	1 to 5, Not known
QF7	Quality of controlling and planning instruments?	1 to 5, Not known

	Products and Services	Grading
QF8	Condition of property and equipment?	1 to 5, Not known
QF9	Quality of products and services offered?	1 to 5, Not known
QF10	Marketing strategy?	1 to 5, Not known
QF11	Organizational structure and workflow?	1 to 5, Not known

	Industry and competitive position	Grading
QF12	State of the industry and industry trends?	1 to 5, Not known
QF13	Competitive position?	1 to 5, Not known
QF14	Dependencies (from customer, vendors etc.) and other special risks?	1 to 5, Not known

	Order backlog	Grading
QF15	Order intake and order backlog	1 to 5, Not known

	Payment history	Grading
QF16	Payment history	1 to 5, Not known

8.2 Measuring Predictive Power

The discriminatory power of qualitative factors can be examined with the concept of "Relative Default Frequency" (RDF). The idea of this concept is to examine the percentage of defaulters in the various grading classes. The higher this percentage in the lower - especially the lowest - grading classes, the stronger the discriminatory power of a factor. An ideal factor would therefore have a RDF of 100% in the lowest grading category and a RDF of 0% in all other categories. For any given grading category, the RDF is calculated as:

$$\text{RDF} = \frac{\textit{number of defaulted companies}}{\textit{total number of companies assigned to this category}}$$

By nature, the RDF cannot provide precise values for the discriminatory power, but rather indicates trends. This is in contrast to the model for quantitative factors as presented in Chapter 6, where the concept of the "Accuracy Ratio" was used to compute the discriminatory power of the individual factors.

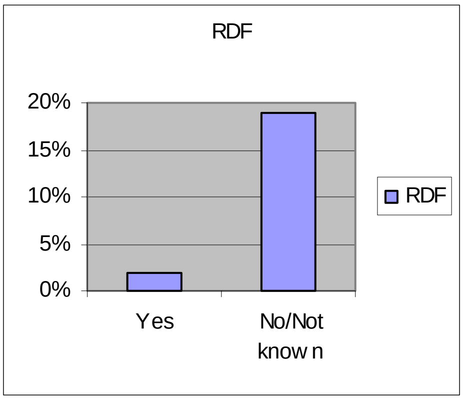
Following are the results for RDF of the individual qualitative factors:

QF1: Business Concept

Table 8.1: RDF of Business Concept

Grading	No of companies	Defaults	RDF
Yes	101	2	2 %
No/Not known	16	3	19 %

Figure 8.1: RDF of Business Concept



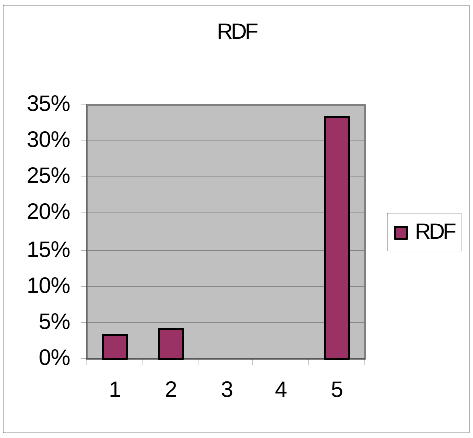
16 of the 117 examined companies did not have a business concept or the account officer did not know of a business concept. Of these 16 companies, 3 companies defaulted. Consequently, the relative default frequency in the No/Not known category is 19%.

QF2: Management Expertise

Table 8.2: RDF of Management Expertise

Grading	No of companies	Defaults	RDF in %
1	60	2	3 %
2	50	2	4 %
3	4	0	0 %
4	0	0	0 %
5/Not known	3	1	33 %

Figure 8.2: RDF of Management Expertise



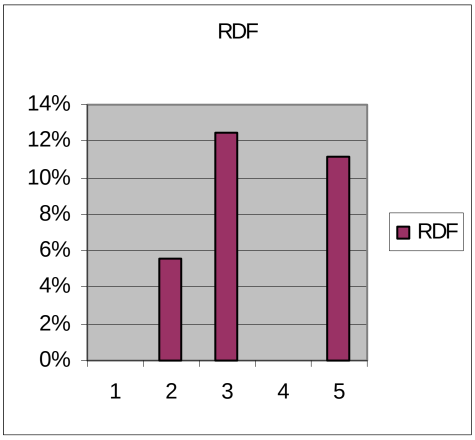
QF2 indicates that the account officers of the bank had strong confidence in the management of the companies they lent to. In as many as 110 cases, the customer's management expertise was graded either 1 or 2. In only three cases, the management expertise was considered weak and graded 5. As one of these 3 companies defaulted, the RDF of the lowest category is 33%.

QF3: Leadership Style

Table 8.3: RDF of Leadership Style

Grading	No of companies	Defaults	RDF in %
1	46	0	0 %
2	54	3	6 %
3	8	1	13 %
4	0	0	0 %
5/Not known	9	1	11 %

Figure 8.3: RDF of Leadership Style



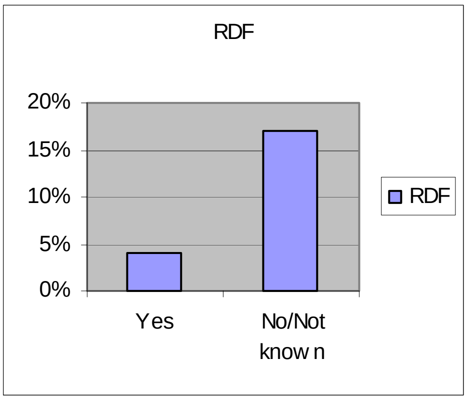
Similar to QF3 but slightly less pronounced is the strength of trust of account officers in the leadership style of the management. In only 9 cases, the leadership style was judged to be bad or was unknown. Given one default, the RDF of this category is a low 14%.

QF4: Management Succession

Table 8.4: RDF of Management Succession

Grading	No of companies	Defaults	RDF in %
Yes	111	4	4 %
No/Not known	6	1	17 %

Figure 8.4: RDF of Management Succession



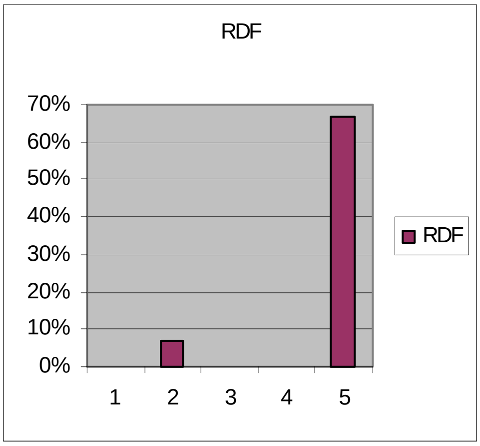
In almost every case, the account officer deemed the management succession to be defined. Only 6 of the 117 companies had not defined, by whom the manager currently in charge would be succeeded. One of the undefined/unknown cases defaulted, resulting in a RDF of 17%.

QF5: Information Policy Towards the Bank

Table 8.5: RDF of Information Policy

Grading	No of companies	Defaults	RDF in %
1	59	0	0 %
2	43	3	7 %
3	10	0	0 %
4	2	0	0 %
5/Not known	3	2	67 %

Figure 8.5: RDF of Information Policy



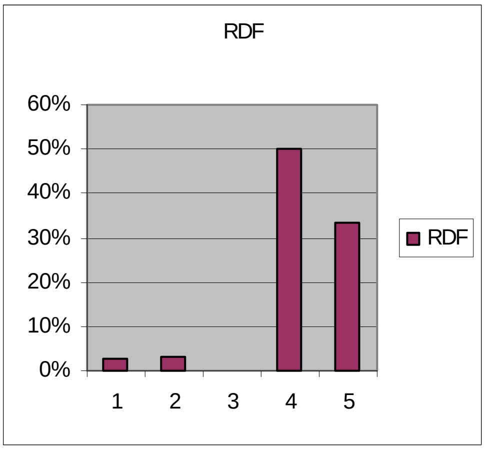
The account officers were apparently satisfied with the way their customers reported information to the bank. 102 of the 117 companies were graded 1 or 2. Three companies reported in an insufficient way, whereby two of these three companies later on defaulted, resulting in a strong RDF of 67%. The RDF of 67% suggest a strong discrimintory power.

QF6: Accounting and Reporting

Table 8.6: RDF of Accounting and Reporting

Grading	No of companies	Defaults	RDF in %
1	37	1	3 %
2	60	2	3 %
3	15	0	0 %
4	2	1	50 %
5/Not known	3	1	33 %

Figure 8.6: RDF of Accounting and Reporting



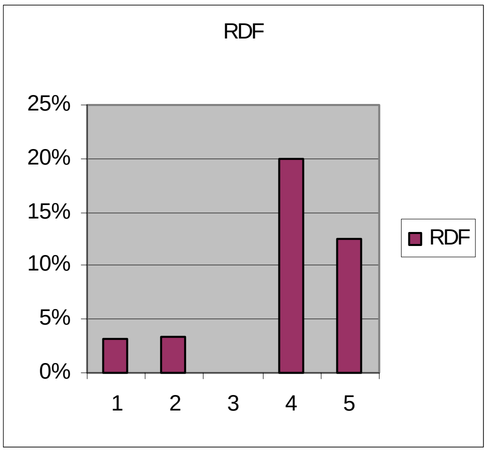
The grades assigned to the quality of accounting and reporting are in line with the previously observed gradings. The majority of companies were conisdered to have a good quality accounting. In 2 cases, the accounting was sub-standard (4) and in three cases, the accounting was considered unsatisfactory and graded 5. One of these three cases defaulted, resulting in an RDF of 33% in grading class 5. The RDF of class 5 is exceeded by the RDF of grading category 4 with 50%.

QF7: Controlling and Planning

Table 8.7: RDF of Controlling and Planning

Grading	No of companies	Defaults	RDF in %
1	32	1	3 %
2	60	2	3 %
3	12	0	0 %
4	5	1	20 %
5/Not known	8	1	13 %

Figure 8.7: RDF of Controlling and Planning



The grades assigned for the quality of controlling and planning were substantially the same as the grades assigned for accounting and reporting. The highest grade was assigned to 32 companies, which compares to 37 companies being assigned the highest grade for accounting quality. A difference can be observed in the lowest grading category. While 8 companies were graded 5 for controlling and planning, only 3 customers were assigned to the lowest grading category. Given that category 5 includes the answer “unknown”, it is not unlikely that the increased number of lowest grades is due to the fact, that the condition of planning and controlling is not known to the account officer.

While customers are most commonly required to deliver financial statements to their lender, therefore disclosing their accounts to the bank and making the quality of their accounting visible, it is much less common for a borrower to disclose its financial planning and controlling to the bank – if there is planning and controlling at all.

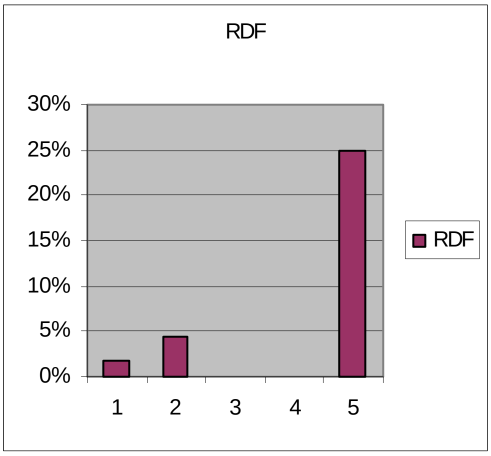
In the sample used in this study, one company in the lowest grading category defaulted. The resulting RDF is a low 13%. In this case, with an RDF of 20%, the RDF of grading category 4 exceeds the RDF of the lowest category.

QF8: Condition of Property and Equipment

Table 8.8: RDF of Condition of Property and Equipment

Grading	No of companies	Defaults	RDF in %
1	58	1	2 %
2	45	2	4 %
3	6	0	0 %
4	0	0	0 %
5/Not known	8	2	25 %

Figure 8.8: RDF of Condition of Property and Equipment



The condition of the property and equipment of the examined companies was mostly considered very good or good. Not less than 103 companies were assigned a grading of either 1 or 2. Interestingly, not a single company was assigned a grading of 3 or 4. However, the lowest grading was assigned to 8 companies, of which 2 companies defaulted. The result is a RDF of 25% for the grading class 5.

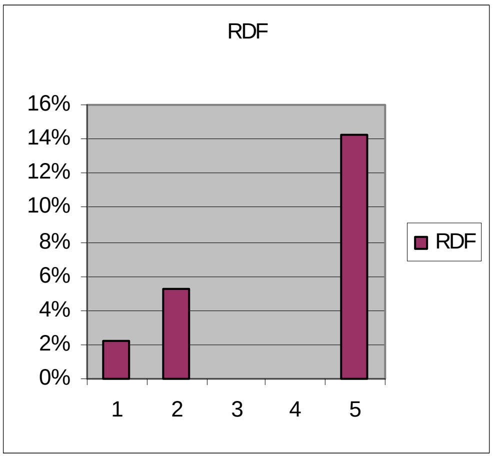
It should be noted that software companies use to own relatively little property and equipment. This was also reflected in the financial analysis of the companies in this study. On average, fixed assets represent a small portion of total assets of the examined software companies.[193]

QF9: Quality of Products and Services

Table 8.9: RDF of Products and Services

Grading	No of companies	Defaults	RDF in %
1	45	1	2 %
2	57	3	5 %
3	8	0	0 %
4	0	0	0 %
5/Not known	7	1	14 %

Figure 8.9: RDF of Products and Services



The account officers in charge of assigning grades were obviously confident about the quality of the products and services, that were offered by their customers. 45 companies were assigned the highest grade and 57 companies were assigned the second-best grade. The products and services of 7 customers were graded to be

[193] see Chapter 7.3.6

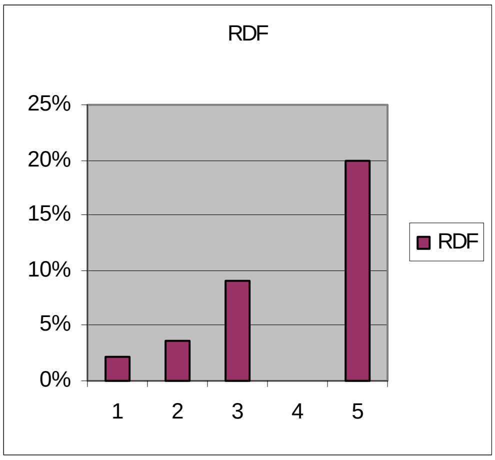
unsatisfactory. One of these customers defaulted. The resulting RDF of the lowest grading category is therefore 14%.

QF10: Marketing Strategy

Table 8.10: RDF of Marketing Strategy

Grading	No of companies	Defaults	RDF in %
1	45	1	2 %
2	56	2	4 %
3	11	1	9 %
4	0	0	0 %
5/Not known	5	1	20 %

Figure 8.10: RDF of Marketing Strategy



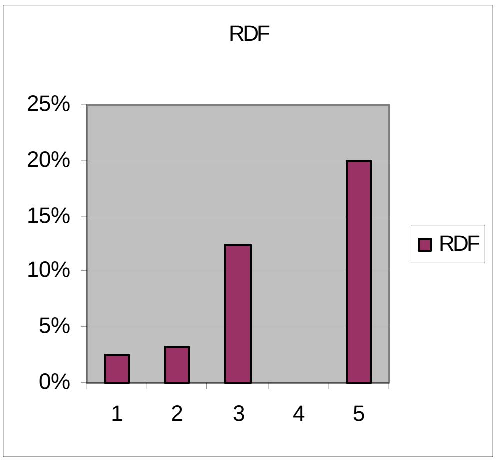
The gradings of the marketing strategy show a picture similar to the gradings of the previous questions. The majority of the companies had – in the account officers' opinion – a very good or good marketing strategy. 5 companies were assigned the lowest grade and one of these companies defaulted. The RDF of category 5 is therefore 20%. Interestingly, the defaults were almost equally allocated to each grading category. The discriminatory power of this qualitative factor is low.

QF11: Organizational Structure and Workflow

Table 8.11: RDF of Organizational Structure and Workflow

Grading	No of companies	Defaults	RDF in %
1	41	1	2 %
2	62	2	3 %
3	8	1	13 %
4	1	0	0 %
5/Not known	5	1	20 %

Figure 8.11: RDF of Organizational Structure and Workflow



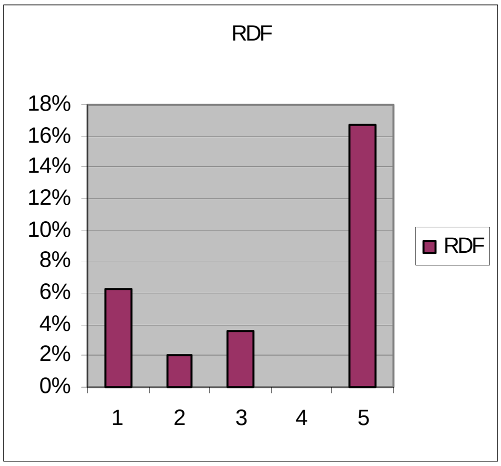
In the majory of the companies, the organizational structure was judged to qualify for a grade of either 1 or 2. 8 companies were assigned the grade 3. The lowest grading category has 5 companies, of which one company defaulted. The RDF of this grading category is therefore 20%. Altogether, the predictive power of the question regarding the organizational structure of the company and the workflow within the company turned out to be modest.

QF12: State of the Industry and Industry Trends

Table 8.12: RDF of State of the Industry and Industry Trends

Grading	No of companies	Defaults	RDF in %
1	32	2	6 %
2	49	1	2 %
3	28	1	4 %
4	2	0	0 %
5/Not known	6	1	17 %

Figure 8.12: RDF of State of the Industry and Industry Trends



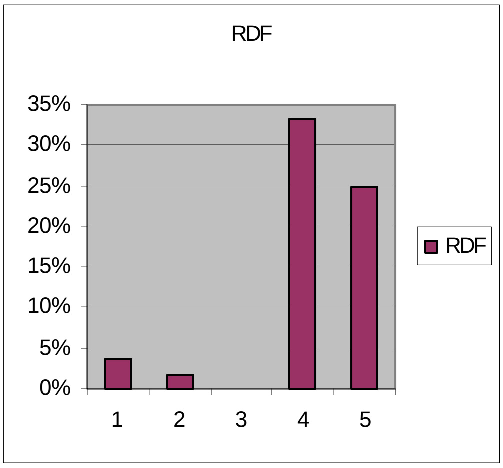
QF12 relates to the state of the software industry as well as industry trends. The results indicate a more moderate judgement of the companies in the sample. Especially, there is a relatively higher number of companies that were assigned to grading category 3. 6 companies were graded 5 and 1 of these 6 companies defaulted. The RDF of the lowest grading class is therefore 17%.

QF13: Competitive Position

Table 8.13: RDF of Competitive Position

Grading	No of companies	Defaults	RDF in %
1	27	1	4 %
2	57	1	2 %
3	22	0	0 %
4	3	1	33 %
5/Not known	8	2	25 %

Figure 8.13: RDF of Competitive Position



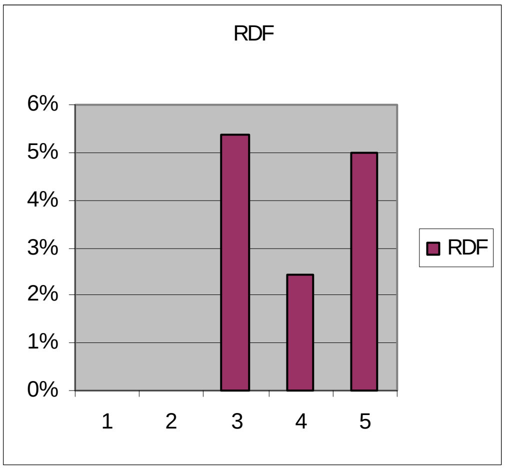
In 27 cases, the account officers considered the competitive position of their customers very strong and assigned a grade of 1. 57 companies were assigned a grade of 2, signalling a strong position in the software industry. The grade 5 was assigned to 8 customers, whereby 2 of these companies defaulted. The RDF of the grading class 5 is therefore 25% and is lower than the RDF of grading category 4, which is 33%.

QF14: Dependencies and Other Special Risks

Table 8.14: RDF of Dependencies and Other Special Risks

Grading	No of companies	Defaults	RDF in %
1	0	0	0 %
2	0	0	0 %
3	56	3	5 %
4	41	1	2 %
5/Not known	20	1	5 %

Figure 8.14: RDF of Dependencies and Other Special Risks



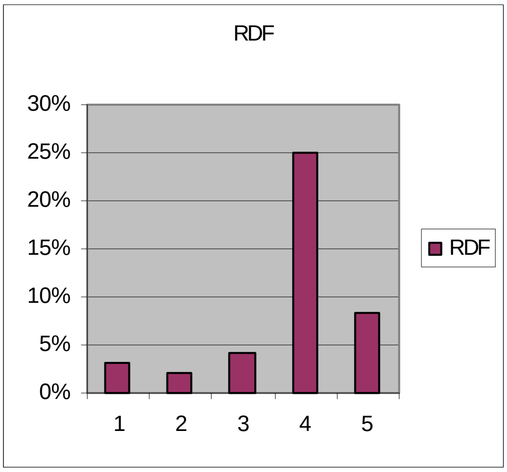
Most obvious, no company was assigned a grade of 1 or 2 in this case. With 56 companies, approximately every other customer was considered to be modestly dependent or to face other special risks. 41 companies were assigned a grade of 4 and 20 companies were assigned a grade of 5. The majority of defaults ocurred in grading class 3, while there was one default each in grading classes 4 and 5. The RDF of grading category 5 is a very low 5%, representing a very weak predictive power of this qualitative factor.

QF15: Order Intake and Order Backlog

Table 8.15: RDF of Order Intake and Order Backlog

Grading	No of companies	Defaults	RDF in %
1	31	1	3 %
2	46	1	2 %
3	24	1	4 %
4	4	1	25 %
5/Not known	12	1	8 %

Table 8.15: RDF of Order Intake and Order Backlog



QF15 addresses the order intake and order backlog of software companies. The results of the judgements of the account officers reflect, that 31 companies were considered to have had a strong order intake and order backlog. 46 companies were assigned a grade of 2, reflecting a good order situation. In 12 cases, the grade assigned was 5. This may indicate, that the information on order intake and backlog was not available to the account officers.

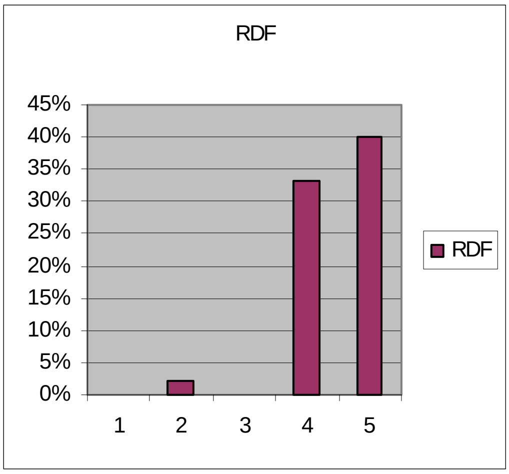
There was one default in each grading category. The RDF of all categories are moderate, whereby grading category 4 has the strongest RDF with 25%. Altogether, the discriminatory power of QF15is weak.

QF16: Payment History

Table 8.16: RDF of Payment History

Grading	No of companies	Defaults	RDF in %
1	0	0	0 %
2	96	2	2 %
3	13	0	0 %
4	3	1	33 %
5/Not known	5	2	40 %

Table 8.16: RDF of Payment History



The payment history turned out to be a strong indicator of default. In no case, the grade 1 was assigned. In sharp contrast, grading category 2 contains 96 companies. 5 customers were assigned the grade 5, resulting in a strong RDF of 40% and indicating a strong predictive power of this qualitative factor.

Examining the results of the qualitative factors, one can identify two trends:

- Altogether, the judgements appear to be rather optimistic. At most of the questions, the majority of companies were assigned either grade 1 or 2.

- The results of the RDF analysis reflect that the RDF of the lowest grading category is in the majority of cases higher than the RDF in the other grading categories. This indicates that most of the individual factors examined in this study do have discriminatory power.

The factor with the strongest predictive power is QF7, which relates to the information policy of customers towards the bank. For this factor, the lowest grading category has a RDF of 67%, while categories 1, 3, and 4 have a RDF of 0% and category 2 has a RDF of 7%. Factors with significant discriminatory power further include QF21, measuring the payment history of customers, as well as QF2, which is intended to examine the existence of a business concept for companies.

8.3 Logistic Regression and Qualitative Model

In line with the modeling process for the quantitative rating, the rating model for qualitative factors was created through a stepwise logistic regression with SPSS. In contrast to the quantitative model, no further selection of qualitative factors for the final modeling process was made, but instead all factors included. The reason is that the concept of RDF cannot provide precise values for the discriminatory power, but rather indicates trends. A selection of qualitative factors according to their RDF would therefore be somewhat subjective and involve the risk of excluding factors, which may have a strong contribution in a rating model. In accordance with the quantitative model, the scores of the qualitative factors were standardized before being used for the regression.

The stepwise selection process as performed with SPSS resulted in the following initial model:

Table 8.17: Initial Qualitative Model

Variable	Coefficient	Significance
Constant	-21.058	0.000
QF16	-3.623	0.001
QF5	-1.712	0.075
QF4	1.269	0.217
QF1	-0.817	0.378
QF12	2.395	0.046
QF8	-3.572	0.019
QF9	1.617	0.151
QF13	-1.486	0.240
QF11	1.693	0.243

The initial model comprises 9 variables with different contributions to the model. In line with the rules applied in for the quantitative model[194], the 4 positive variables were excluded in order to make the rating system plausible and reasonably comprehensible for practical users. A new logistic regression without the excluded negative variables resulted in the following final model:

Table 8.18: Final Qualitative Model

Variable	Coefficient	Significance
Constant	-21.058	0.000
QF16	-2.307	0.013
QF5	-1.778	0.066
QF1	-1.094	0.246
QF8	-0.306	0.752

The model consists of four variables. QF13 was excluded by SPSS. The variable with the strongest contribution to the model is QF16, measuring the payment history of the customers. The related significance of this ratio is 0.013. The second highest weight has QF5, examining the customers' information policy towards the bank. The respective significance is 0.066. The final rating model further

[194] see chapter 6.7

includes QF1, which reflects the appraisal of a company´s business concept, as well as factor QF8, which captures the condition of property and equipment.

The final qualitative rating model was applied to the data set at hand and tested for rating accuracy. The result is an AR of 73%. The discriminatory power of the qualitative model is therefore stronger than the power of the quantitative model.

Pursuant to the results of the qualitative rating model, one may conclude that a software company´s default probability decreases

- the better its payment history is
- the better its information policy towards the bank is
- when the company has a business model with defined goals and a respective strategy
- the better the condition of its property and equipment is

It appears that the more quantifiable a qualitative factor is, the higher its discriminatory power. Payment history can be made somewhat quantifiable by evaluation of the account information.[195] For example, the more often a company exceeds its credit limit, the worse an account officer will most likely grade a company´s payment history. Information policy may be made quantifiable by evaluating how many times a customer did not comply with its obligatory reporting requirements (e.g. delivery of financial statements). The existence of a business concept may be easy to examine by investigating if a company has a written business strategy.

[195] for a comprehensive discussion of the evaluation of credit risk through account information see Maderbacher, M., Dynamische Kontendatenanalyse zur Risikofrüherkennung unter Anwendung statistischer Prozeßkontrolltechnik, 1999

Chapter 9

Combined Rating Model

Subsequent to completion of the quantitative and the qualitative rating model, a third model was created through the combination of the quantitative and the qualitative model. The combined model is a weighted combination of the outcomes of the quantitative and the qualitative model. Therefore, it includes the following variables:

Table 9.1: Combined Model

Variable	Coefficient	Significance
C2	- 1.814	0.045
P4	- 1.205	0.183
PR1	-0.604	0.605
A4	- 0.887	0.304
QF16	-2.307	0.013
QF5	-1.778	0.066
QF1	-1.094	0.246
QF8	-0.306	0.752

The combined model was applied to the data set and tested for predictive power. The author further examined the impact of changing the weights of the two individual models on the predictive power of the combined model. Testing different combinations had the following results:

Table 9.2: Weights and Predictive Power

Weight Quantitative Model	Weight Qualitative Model	Accuracy Ratio
10 %	90 %	73 %
20 %	80 %	75 %
30 %	70 %	76 %
40 %	60 %	76 %
50 %	50 %	76 %
60 %	40 %	75 %
70 %	30 %	75 %
80 %	20 %	75 %
90 %	10 %	73 %

The variation of weights for the combined model shows, that the strongest predictive power is derived when the weights of the individual models range between 30%/70% and 50%/50%. The predictive power of the model deteriorates when the quantitative model is weighted lower than 30% or higher than 50%.

The result of this combination is an improvement of discriminatory power to 76%, which compares to individual AR of 67.5% for the quantitative model and 73% for the qualitative model, respectively.

Chapter 10

Summary and Conclusion

Since the time lending was invented, lenders have faced credit risk, i.e. the risk that the borrower does not repay the loan. Various techniques were developed over time in a constant effort to limit credit risk. Most commonly used methodologies have been human expert systems, which are based on the experience, knowledge and skills of employees of financial institutions. A more recent approach is the application of credit risk models, which use statistical methodologies, such as discriminant analysis, logistic regression, or neural networks, to estimate the probability of default. Credit risk models are based on historical information on companies. In most cases, these models are based on accounting data.

However, credit risk models which use only historical accounting data have certain limitations. Main limitations include the historical character of book values, the incompleteness of accounting data, and the distortion of consistency when different accounting standards were applied to the accounting data set. The major point of critcism, however, is that accounting data does not represent the value of companies, as parts of a company´s potential are not reflected by historical financial figures. Critics point out that intangible values such as intellectual capital, management skills, knowledge and other forms of soft skills are not accurately expressed in traditional balance sheets. The limitations of accounting data become particularly evident when it comes to judging the value or financial conditon of firms where knowledge represents their key value. Examples of such firms are software companies.

The collapse of the "New Economy" and the bankruptcy of numerous software companies has resulted in huge loan losses at financial institutions and has evidenced that credit risk of lending to software companies was underestimated. Apparently, the methodologies that had been applied for default prediction were insufficient. Consequently, better techniques for default prediction for software companies need to be developed. Even more so, that "Basel II", the New Capital Accord proposed by the “Basel Committee on Banking Supervision”, is expected to be implemented. Banks applying Basel II will have to opt for one of three approaches for the estimation of credit risk, the "Standardized Approach", the "Foundation IRB Approach", or the "Advanced IRB Approach". If a bank opts for one of the IRB approaches, it will be required to have a technique with which it can accurately estimate the probability of default of its credit portfolio. This portfolio may include exposure to software firms.

The goal of this dissertation was the creation of a credit risk model which can be used by lenders to predict the default of Austrian software companies. A prerequisite for reliability and accuracy was deemed to be data consistency. Therefore, only data on companies operating in the software industry and being located in Austria was used as input in the modeling process. This data was provided by a major Austrian commercial bank.

The author used three approaches in order to create the model with the strongest predictive power. In a first approach, a model was created which was based solely on accounting data. Financial ratios were defined to examine those areas of a company which are considered significant from a credit perspective. Areas examined in this study include Profitability, Capital Structure, Liquidity, Debt

Service Coverage, Productivity, Activity, Asset Quality, Growth, and Size. The financial ratios were then applied to the data set. An explorative analysis of the results followed, in which means and standard deviations of defaulted and non-defaulted companies were compared for each ratio. Certain trends were indicated, whereby the most obvious trends were as follows: non-defaulted companies were profitable, whereas defaulted companies posted losses; non-defaulted firms had positive book equity, while the average book equity of defaulted firms was negative; non-defaulted companies had positive debt service coverage, whereby defaulted companies did not generate enough cash to cover debt payments; non-defaulted firms also prevailed in terms of liquidity and productivity.

The results of the ratio calculations were subsequently used as independent variables in a logistic regression model. The final model included four ratios and identified the following areas as the most significant for the creditworthiness of a software company: capital structure, profitability, productivity, and accounts receivable management. The predictive power of the model was measured with the concept of the Cumulative Accuracy Profile (CAP), which assigned a predictive power of 67.5% to the quantitative model. The predictive power of this model is in line with the power of models created in similar studies and can be deemed acceptable for actual application.

In a second approach, a credit risk model was created which was based entirely on qualitative information. The input of this model was the result of an evaluation and appraisal of certain aspects of software companies, including management skills, quality of accounting, quality of products and services, competitive position, order backlog, and payment history. The evaluation was given in the form of a grading. The study subsequently examined the percentage of defaulters in the various grading classes. It turned out that the relative default frequency in the lowest grading category was in the majority of cases higher then the relative default frequency in the higher grading categories. It is therefore indicated, that the grading of qualitative aspects of software companies has discriminatory power.

The gradings were then used as variables for a logistic regression model. The final model includes four variables, being payment history, information policy, business model, and the company´s property. The predictive power of the qualitative model was tested with the CAP concept, which resulted a predictive power of 73%. The predictive power of the qualitative model is therefore stronger than the predictive power of the quantitative model.

In a third approach, the quantitative and the qualitative models were combined in order to find out if a combined model would have a stronger predictive power than the individual models. The combination resulted in a model with a power of 76%.

The results of this dissertation indicate that a credit risk model for Austrian software companies, which is based solely on accounting data, can have an acceptable predictive power, if the model is based on consistent data. Likewise, a model based entirely on qualitative information can result in acceptable predictive power. As the results of this study suggest, the power of a qualitative model for software companies can even exceed the power of a quantitative model for software companies. A combination of quantitative and qualitative variables has turned out to be the best approach, as the predictive power of the combined model exceeds the power of both individual models.

The study indicates the advantage of an industry focus versus creating a model based on companies from different industries. The predicitve power of the quantitative model created in this study is significantly stronger than the power of quantitative models without industry focus as presented in other studies.

Appendix: Correlation Matrix – Table 1

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	S1	S2	P1	P2	P3	P4	P5	P6	L1
G1	1.00	0.39	0.35	0.48	0.67	0.55	0.67	0.49	0.18	-0.21	0.21	-0.25	-0.01	0.11	0.33	0.23	0.35	-0.05	-0.06	-0.18	0.08
G2	0.39	1.00	0.77	0.67	0.43	0.22	0.43	0.38	-0.01	-0.16	-0.03	-0.14	-0.04	-0.02	0.11	0.08	0.13	-0.08	-0.09	-0.03	0.05
G3	0.35	0.77	1.00	0.25	0.35	0.32	0.34	0.46	-0.01	-0.08	-0.04	-0.06	-0.09	-0.04	0.12	0.13	0.16	-0.15	-0.16	-0.12	0.03
G4	0.48	0.67	0.25	1.00	0.74	0.09	0.74	0.61	-0.01	-0.32	-0.03	-0.31	-0.01	-0.01	0.16	0.07	0.17	-0.06	-0.06	-0.03	0.12
G5	0.67	0.43	0.35	0.74	1.00	0.18	0.98	0.86	0.00	-0.37	0.00	-0.39	-0.05	-0.01	0.38	0.25	0.38	0.09	0.08	0.04	0.11
G6	0.55	0.22	0.32	0.09	0.18	1.00	0.15	0.09	-0.01	-0.04	0.04	-0.07	-0.06	0.02	-0.03	-0.03	0.00	-0.40	-0.41	-0.52	0.02
G7	0.67	0.43	0.34	0.74	0.98	0.15	1.00	0.81	0.00	-0.39	0.00	-0.38	-0.02	-0.01	0.42	0.31	0.43	0.14	0.14	0.10	0.14
G8	0.49	0.38	0.46	0.61	0.86	0.09	0.81	1.00	0.13	-0.30	0.12	-0.29	-0.12	-0.02	0.20	0.10	0.19	-0.02	-0.03	-0.04	-0.01
G9	0.18	-0.01	-0.01	-0.01	0.00	-0.01	0.00	0.13	1.00	-0.02	1.00	0.00	0.06	0.43	-0.01	0.01	-0.03	0.03	0.01	0.03	0.12
G10	-0.21	-0.16	-0.08	-0.32	-0.37	-0.04	-0.39	-0.30	-0.02	1.00	-0.05	0.33	0.04	0.06	-0.18	-0.14	-0.18	-0.08	-0.07	-0.06	-0.03
G11	0.21	-0.03	-0.04	-0.03	0.00	0.04	0.00	0.12	1.00	-0.05	1.00	0.04	0.06	0.43	-0.02	0.01	-0.03	0.03	0.01	0.04	0.14
G12	-0.25	-0.14	-0.06	-0.31	-0.39	-0.07	-0.38	-0.29	0.00	0.33	0.04	1.00	0.03	0.03	-0.20	-0.14	-0.19	-0.06	-0.06	-0.03	-0.05
S1	-0.01	-0.04	-0.09	-0.01	-0.05	-0.06	-0.02	-0.12	0.06	0.04	0.06	0.03	1.00	1.00	0.12	0.10	0.11	0.01	0.01	0.01	0.02
S2	0.11	-0.02	-0.04	-0.01	-0.01	0.02	-0.01	-0.02	0.43	0.06	0.43	0.03	1.00	1.00	0.11	0.10	0.11	0.01	0.01	0.01	0.02
P1	0.33	0.11	0.12	0.16	0.38	-0.03	0.42	0.20	-0.01	-0.18	-0.02	-0.20	0.12	0.11	1.00	0.97	0.95	0.44	0.44	0.45	0.28
P2	0.23	0.08	0.13	0.07	0.25	-0.03	0.31	0.10	0.01	-0.14	0.01	-0.14	0.10	0.10	0.97	1.00	0.91	0.43	0.43	0.44	0.30
P3	0.35	0.13	0.16	0.17	0.38	0.00	0.43	0.19	-0.03	-0.18	-0.03	-0.19	0.11	0.11	0.95	0.91	1.00	0.46	0.46	0.46	0.09
P4	-0.05	-0.08	-0.15	-0.06	0.09	-0.40	0.14	-0.02	0.03	-0.08	0.03	-0.06	0.01	0.01	0.44	0.43	0.46	1.00	1.00	1.00	0.05
P5	-0.06	-0.09	-0.16	-0.06	0.08	-0.41	0.14	-0.03	0.01	-0.07	0.01	-0.06	0.01	0.01	0.44	0.43	0.46	1.00	1.00	1.00	0.05
P6	-0.18	-0.03	-0.12	-0.03	0.04	-0.52	0.10	-0.04	0.03	-0.06	0.04	-0.03	0.01	0.01	0.45	0.44	0.46	1.00	1.00	1.00	0.07
L1	0.08	0.05	0.03	0.12	0.11	0.02	0.14	-0.01	0.12	-0.03	0.14	-0.05	0.02	0.02	0.28	0.30	0.09	0.05	0.05	0.07	1.00
L2	0.07	0.06	0.03	0.14	0.14	0.01	0.16	0.02	-0.06	-0.05	-0.07	-0.11	0.00	0.00	0.31	0.31	0.11	0.05	0.05	0.06	0.92
L3	0.17	0.08	0.00	0.17	0.18	0.06	0.19	0.02	-0.08	-0.05	-0.07	-0.07	-0.03	-0.03	0.25	0.24	0.03	0.02	0.02	0.04	0.89
L4	-0.02	-0.05	0.00	-0.04	-0.07	-0.02	0.00	-0.10	-0.02	0.02	-0.02	0.00	-0.01	0.00	0.06	0.07	0.07	0.02	0.02	0.02	-0.02
C1	0.15	0.16	0.11	0.16	0.11	0.17	0.20	0.02	0.17	-0.09	0.18	-0.07	0.09	0.09	0.26	0.29	0.24	0.17	0.17	0.17	0.54
C2	0.15	0.16	0.11	0.16	0.11	0.17	0.20	0.02	0.16	-0.08	0.18	-0.07	0.09	0.09	0.27	0.29	0.24	0.17	0.17	0.17	0.54
C3	0.15	0.16	0.11	0.16	0.11	0.17	0.20	0.02	0.17	-0.09	0.18	-0.07	0.09	0.09	0.26	0.29	0.24	0.17	0.17	0.17	0.54
C4	0.15	0.16	0.11	0.16	0.11	0.17	0.20	0.02	0.16	-0.08	0.18	-0.07	0.09	0.09	0.27	0.29	0.24	0.17	0.17	0.17	0.54
C5	0.15	0.16	0.11	0.17	0.12	0.15	0.20	0.03	0.16	-0.10	0.18	-0.07	0.09	0.09	0.27	0.29	0.23	0.16	0.16	0.16	0.54
C6	0.15	0.16	0.12	0.17	0.12	0.15	0.20	0.03	0.16	-0.09	0.17	-0.07	0.09	0.09	0.27	0.29	0.23	0.16	0.16	0.16	0.54
C7	0.12	-0.14	-0.11	-0.02	0.05	-0.04	-0.14	0.08	-0.03	0.18	-0.05	-0.14	0.06	0.07	-0.10	-0.15	-0.11	-0.12	-0.11	-0.15	-0.43
C8	-0.41	-0.34	-0.17	-0.50	-0.61	-0.16	-0.64	-0.38	0.04	0.29	0.04	0.20	0.01	0.01	-0.23	-0.16	-0.21	0.01	0.01	0.01	-0.31

Appendix: Correlation Matrix – Table 2

	G1	G2	G3	G4	G5	G6	G7	G8	G9	G10	G11	G12	S1	S2	P1	P2	P3	P4	P5	P6	L1
C9	-0.02	-0.05	-0.16	0.05	-0.22	0.01	-0.10	-0.20	0.00	-0.03	0.01	-0.03	0.00	-0.01	0.20	0.21	0.21	0.13	0.14	0.16	-0.08
C10	0.09	0.07	0.07	0.12	0.11	0.04	0.11	0.07	0.02	0.45	0.01	-0.05	-0.01	-0.01	0.11	0.07	0.12	0.00	0.00	0.00	-0.05
C11	-0.02	-0.05	-0.16	0.05	-0.22	0.01	-0.10	-0.20	0.00	-0.03	0.01	-0.03	0.00	-0.01	0.20	0.21	0.21	0.13	0.14	0.16	-0.08
C12	0.09	0.07	0.07	0.12	0.11	0.04	0.11	0.07	0.02	0.45	0.01	-0.05	-0.01	-0.01	0.11	0.07	0.12	0.00	0.00	0.00	-0.05
C13	0.36	-0.23	-0.19	-0.19	-0.08	-0.13	-0.18	-0.06	-0.05	0.11	-0.05	-0.02	-0.03	-0.02	0.02	0.01	0.00	0.00	0.01	0.02	-0.23
C14	0.08	-0.20	-0.17	-0.16	-0.14	-0.14	-0.20	-0.08	-0.03	0.13	-0.04	0.04	-0.02	-0.02	-0.06	-0.05	-0.06	0.02	0.02	0.02	-0.15
D1	0.02	-0.04	0.05	-0.13	0.03	0.02	0.04	0.03	-0.03	0.02	-0.03	-0.01	0.37	0.36	0.59	0.57	0.59	0.47	0.47	0.47	0.17
D2	-0.02	-0.02	-0.06	0.02	0.02	-0.02	0.06	-0.03	0.10	0.01	0.09	-0.06	-0.55	-0.54	0.08	0.10	0.06	0.09	0.07	0.09	0.05
D3	0.03	-0.02	-0.04	0.02	-0.01	0.02	0.00	-0.02	0.12	0.04	0.11	-0.05	-0.04	-0.06	-0.11	-0.15	0.04	-0.01	-0.01	-0.03	-0.56
D4	0.05	-0.09	-0.15	0.02	0.02	0.01	0.12	0.02	0.26	0.00	0.26	-0.04	-0.33	-0.32	0.12	0.16	0.12	0.16	0.14	0.16	0.06
D5	0.05	-0.08	-0.11	0.00	-0.03	0.03	-0.01	-0.01	0.22	0.07	0.22	-0.03	-0.04	-0.05	0.03	0.02	0.03	0.00	0.00	0.00	-0.02
D6	-0.02	-0.02	-0.06	0.02	0.02	-0.02	0.06	-0.03	0.10	0.01	0.09	-0.06	-0.55	-0.54	0.08	0.10	0.06	0.09	0.07	0.09	0.05
D7	0.03	-0.02	-0.04	0.02	-0.01	0.02	0.00	-0.02	0.12	0.04	0.11	-0.05	-0.04	-0.06	-0.11	-0.15	0.04	-0.01	-0.01	-0.03	-0.56
D8	0.05	-0.09	-0.15	0.02	0.02	0.01	0.12	0.02	0.26	0.00	0.26	-0.04	-0.33	-0.32	0.12	0.16	0.12	0.16	0.14	0.16	0.06
D9	0.05	-0.08	-0.11	0.00	-0.03	0.03	-0.01	-0.01	0.22	0.07	0.22	-0.03	-0.04	-0.05	0.03	0.02	0.03	0.00	0.00	0.00	-0.02
PR1	0.04	0.29	-0.01	0.07	0.03	-0.03	0.10	-0.01	0.00	0.05	0.00	0.05	0.99	0.97	0.15	0.14	0.14	0.02	0.02	0.02	0.09
PR2	0.58	0.35	0.11	0.47	0.58	0.40	0.63	0.44	0.06	-0.25	0.05	-0.43	0.99	0.97	0.15	0.15	0.14	0.02	0.02	0.02	0.21
PR3	0.47	0.31	0.73	0.51	0.35	0.10	0.39	0.47	0.30	0.54	0.36	0.01	0.02	-0.32	0.01	0.99	0.97	0.15	0.15	0.14	0.02
PR4	0.48	0.26	0.65	0.48	0.27	0.03	0.37	0.44	0.41	0.48	0.32	0.09	0.09	-0.35	0.09	0.99	0.97	0.15	0.15	0.14	0.02
PR5	-0.15	0.01	0.38	0.08	0.14	0.07	0.14	0.23	-0.13	-0.01	-0.13	0.06	1.00	1.00	0.15	0.14	0.13	0.02	0.02	0.02	0.21
PR6	-0.05	-0.17	0.20	-0.32	-0.02	-0.01	-0.03	0.11	0.01	-0.01	0.02	0.04	-0.02	-0.02	0.09	0.10	0.06	0.17	0.17	0.17	0.04
PR7	0.20	0.07	0.17	0.17	0.19	0.04	0.17	0.22	-0.10	-0.14	-0.09	-0.15	1.00	1.00	0.15	0.14	0.14	0.02	0.02	0.02	0.21
A1	0.22	-0.27	-0.18	-0.19	-0.07	0.57	-0.09	-0.10	0.11	0.11	0.22	0.01	-0.02	-0.02	-0.44	-0.43	-0.47	-0.99	-0.99	-0.99	-0.01
A2	0.11	-0.13	-0.05	-0.09	-0.07	0.32	-0.04	-0.07	0.16	0.10	0.20	-0.01	-0.02	-0.02	-0.37	-0.36	-0.43	-0.83	-0.83	-0.83	0.11
A3	0.05	-0.09	-0.05	-0.05	-0.01	0.58	-0.03	-0.04	0.10	0.04	0.21	0.00	-0.02	-0.02	-0.43	-0.42	-0.47	-0.98	-0.98	-0.97	0.07
A5	-0.24	-0.13	-0.16	-0.12	-0.08	-0.17	-0.09	-0.05	0.00	0.04	0.00	-0.06	-0.01	-0.02	-0.02	0.00	-0.03	0.09	0.17	0.09	0.15
A6	0.01	-0.05	-0.11	0.12	0.03	0.08	0.03	0.02	0.01	-0.23	0.02	-0.17	-0.06	-0.06	-0.15	-0.15	-0.13	0.04	0.04	0.04	-0.07
A7	-0.07	-0.10	-0.10	-0.11	-0.21	-0.10	-0.17	-0.17	0.39	-0.02	0.43	-0.03	-0.02	-0.01	0.09	0.06	0.07	-0.01	0.00	-0.02	-0.01
Q1	-0.05	-0.03	-0.12	-0.11	-0.12	0.02	-0.10	-0.11	0.13	0.12	0.20	0.04	-0.05	-0.05	-0.05	-0.04	-0.02	0.04	0.04	0.04	-0.03
Q4	0.22	-0.14	-0.20	0.04	-0.33	0.20	0.04	-0.40	-0.28	-0.14	0.15	0.02	-0.15	-0.16	0.23	0.24	0.19	0.15	0.14	0.15	-0.09
Q5	0.13	0.05	0.00	-0.05	-0.03	0.12	0.00	0.05	0.28	0.11	0.30	0.03	-0.02	-0.02	-0.06	-0.04	-0.06	-0.04	-0.03	-0.04	0.13

Appendix: Correlation Matrix – Table 3

	L2	L3	L4	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	D1	D2	D3	D4
G1	0.07	0.17	-0.02	0.15	0.15	0.15	0.15	0.15	0.15	0.12	-0.41	-0.02	0.09	-0.02	0.09	0.36	0.08	0.02	-0.02	0.03	0.05
G2	0.06	0.08	-0.05	0.16	0.16	0.16	0.16	0.16	0.16	-0.14	-0.34	-0.05	0.07	-0.05	0.07	-0.23	-0.20	-0.04	-0.02	-0.02	-0.09
G3	0.03	0.00	0.00	0.11	0.11	0.11	0.11	0.11	0.12	-0.11	-0.17	-0.16	0.07	-0.16	0.07	-0.19	-0.17	0.05	-0.06	-0.04	-0.15
G4	0.14	0.17	-0.04	0.16	0.16	0.16	0.16	0.17	0.17	-0.02	-0.50	0.05	0.12	0.05	0.12	-0.19	-0.16	-0.13	0.02	0.02	0.02
G5	0.14	0.18	-0.07	0.11	0.11	0.11	0.11	0.12	0.12	0.05	-0.61	-0.22	0.11	-0.22	0.11	-0.08	-0.14	0.03	0.02	-0.01	0.02
G6	0.01	0.06	-0.02	0.17	0.17	0.17	0.17	0.15	0.15	-0.04	-0.16	0.01	0.04	0.01	0.04	-0.13	-0.14	0.02	-0.02	0.02	0.01
G7	0.16	0.19	0.00	0.20	0.20	0.20	0.20	0.20	0.20	-0.14	-0.64	-0.10	0.11	-0.10	0.11	-0.18	-0.20	0.04	0.06	0.00	0.12
G8	0.02	0.02	-0.10	0.02	0.02	0.02	0.02	0.03	0.03	0.08	-0.38	-0.20	0.07	-0.20	0.07	-0.06	-0.08	0.03	-0.03	-0.02	0.02
G9	-0.06	-0.08	-0.02	0.17	0.16	0.17	0.16	0.16	0.16	-0.03	0.04	0.00	0.02	0.00	0.02	-0.05	-0.03	-0.03	0.10	0.12	0.26
G10	-0.05	-0.05	0.02	-0.09	-0.08	-0.09	-0.08	-0.10	-0.09	0.18	0.29	-0.03	0.45	-0.03	0.45	0.11	0.13	0.02	0.01	0.04	0.00
G11	-0.07	-0.07	-0.02	0.18	0.18	0.18	0.18	0.18	0.17	-0.05	0.04	0.01	0.01	0.01	0.01	-0.05	-0.04	-0.03	0.09	0.11	0.26
G12	-0.11	-0.07	0.00	-0.07	-0.07	-0.07	-0.07	-0.07	-0.07	-0.14	0.20	-0.03	-0.05	-0.03	-0.05	-0.02	0.04	-0.01	-0.06	-0.05	-0.04
S1	0.00	-0.03	-0.01	0.09	0.09	0.09	0.09	0.09	0.09	0.06	0.01	0.00	-0.01	0.00	-0.01	-0.03	-0.02	0.37	-0.55	-0.04	-0.33
S2	0.00	-0.03	0.00	0.09	0.09	0.09	0.09	0.09	0.09	0.07	0.01	-0.01	-0.01	-0.01	-0.01	-0.02	-0.02	0.36	-0.54	-0.06	-0.32
P1	0.31	0.25	0.06	0.26	0.27	0.26	0.27	0.27	0.27	-0.10	-0.23	0.20	0.11	0.20	0.11	0.02	-0.06	0.59	0.08	-0.11	0.12
P2	0.31	0.24	0.07	0.29	0.29	0.29	0.29	0.29	0.29	-0.15	-0.16	0.21	0.07	0.21	0.07	0.01	-0.05	0.57	0.10	-0.15	0.16
P3	0.11	0.03	0.07	0.24	0.24	0.24	0.24	0.23	0.23	-0.11	-0.21	0.21	0.12	0.21	0.12	0.00	-0.06	0.59	0.06	0.04	0.12
P4	0.05	0.02	0.02	0.17	0.17	0.17	0.17	0.16	0.16	-0.12	0.01	0.13	0.00	0.13	0.00	0.00	0.02	0.47	0.09	-0.01	0.16
P5	0.05	0.02	0.02	0.17	0.17	0.17	0.17	0.16	0.16	-0.11	0.01	0.14	0.00	0.14	0.00	0.01	0.02	0.47	0.07	-0.01	0.14
P6	0.06	0.04	0.02	0.17	0.17	0.17	0.17	0.16	0.16	-0.15	0.01	0.16	0.00	0.16	0.00	0.02	0.02	0.47	0.09	-0.03	0.16
L1	0.92	0.89	-0.02	0.54	0.54	0.54	0.54	0.54	0.54	-0.43	-0.31	-0.08	-0.05	-0.08	-0.05	-0.23	-0.15	0.17	0.05	-0.56	0.06
L2	1.00	0.95	-0.03	0.47	0.47	0.47	0.47	0.47	0.47	-0.38	-0.35	-0.09	-0.06	-0.09	-0.06	-0.19	-0.15	0.17	0.08	-0.55	0.05
L3	0.95	1.00	-0.03	0.36	0.35	0.36	0.35	0.35	0.35	-0.24	-0.37	-0.03	-0.03	-0.03	-0.03	-0.11	-0.11	0.07	0.11	-0.60	0.02
L4	-0.03	-0.03	1.00	0.05	0.10	0.05	0.10	0.08	0.12	0.08	0.15	-0.12	-0.01	-0.12	-0.01	-0.01	0.02	0.00	0.08	0.06	0.07
C1	0.47	0.36	0.05	1.00	1.00	1.00	1.00	0.97	0.97	-0.61	-0.42	-0.08	-0.13	-0.08	-0.13	-0.42	-0.42	0.27	0.11	-0.12	0.13
C2	0.47	0.35	0.10	1.00	1.00	1.00	1.00	0.97	0.97	-0.60	-0.42	-0.08	-0.13	-0.08	-0.13	-0.42	-0.42	0.27	0.11	-0.12	0.13
C3	0.47	0.36	0.05	1.00	1.00	1.00	1.00	0.97	0.97	-0.61	-0.42	-0.08	-0.13	-0.08	-0.13	-0.42	-0.42	0.27	0.11	-0.12	0.13
C4	0.47	0.35	0.10	1.00	1.00	1.00	1.00	0.97	0.97	-0.60	-0.42	-0.08	-0.13	-0.08	-0.13	-0.42	-0.42	0.27	0.11	-0.12	0.13
C5	0.47	0.35	0.08	0.97	0.97	0.97	0.97	1.00	1.00	-0.57	-0.41	-0.09	-0.13	-0.09	-0.13	-0.39	-0.39	0.26	0.20	-0.07	0.20
C6	0.47	0.35	0.12	0.97	0.97	0.97	0.97	1.00	1.00	-0.56	-0.41	-0.09	-0.13	-0.09	-0.13	-0.39	-0.39	0.26	0.20	-0.07	0.19
C7	-0.38	-0.24	0.08	-0.61	-0.60	-0.61	-0.60	-0.57	-0.56	1.00	0.78	0.25	0.27	0.25	0.27	0.60	0.61	-0.22	-0.09	0.01	-0.02
C8	-0.35	-0.37	0.15	-0.42	-0.42	-0.42	-0.42	-0.41	-0.41	0.78	1.00	0.13	0.00	0.13	0.00	0.45	0.44	-0.13	-0.12	0.07	-0.01

Appendix: Correlation Matrix – Table 4

	L2	L3	L4	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	D1	D2	D3	D4
C9	-0.09	-0.03	-0.12	-0.08	-0.08	-0.08	-0.08	-0.09	-0.09	0.25	0.13	1.00	0.57	1.00	0.57	0.32	0.32	0.00	-0.05	-0.02	-0.13
C10	-0.06	-0.03	-0.01	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	0.27	0.00	0.57	1.00	0.57	1.00	0.23	0.19	0.02	-0.08	0.03	-0.18
C11	-0.09	-0.03	-0.12	-0.08	-0.08	-0.08	-0.08	-0.09	-0.09	0.25	0.13	1.00	0.57	1.00	0.57	0.32	0.32	0.00	-0.05	-0.02	-0.13
C12	-0.06	-0.03	-0.01	-0.13	-0.13	-0.13	-0.13	-0.13	-0.13	0.27	0.00	0.57	1.00	0.57	1.00	0.23	0.19	0.02	-0.08	0.03	-0.18
C13	-0.19	-0.11	-0.01	-0.42	-0.42	-0.42	-0.42	-0.39	-0.39	0.60	0.45	0.32	0.23	0.32	0.23	1.00	0.97	-0.03	-0.22	-0.18	-0.20
C14	-0.15	-0.11	0.02	-0.42	-0.42	-0.42	-0.42	-0.39	-0.39	0.61	0.44	0.32	0.19	0.32	0.19	0.97	1.00	-0.06	-0.22	-0.11	-0.20
D1	0.17	0.07	0.00	0.27	0.27	0.27	0.27	0.26	0.26	-0.22	-0.13	0.00	0.02	0.00	0.02	-0.03	-0.06	1.00	0.03	-0.01	0.05
D2	0.08	0.11	0.08	0.11	0.11	0.11	0.11	0.20	0.20	-0.09	-0.12	-0.05	-0.08	-0.05	-0.08	-0.22	-0.22	0.03	1.00	0.53	0.72
D3	-0.55	-0.60	0.06	-0.12	-0.12	-0.12	-0.12	-0.07	-0.07	0.01	0.07	-0.02	0.03	-0.02	0.03	-0.18	-0.11	-0.01	0.53	1.00	0.30
D4	0.05	0.02	0.07	0.13	0.13	0.13	0.13	0.20	0.19	-0.02	-0.01	-0.13	-0.18	-0.13	-0.18	-0.20	-0.20	0.05	0.72	0.30	1.00
D5	-0.03	-0.04	0.03	-0.01	-0.01	-0.01	-0.01	0.03	0.03	0.10	0.13	-0.10	-0.01	-0.10	-0.01	-0.14	-0.12	-0.06	0.25	0.56	0.51
D6	0.08	0.11	0.08	0.11	0.11	0.11	0.11	0.20	0.20	-0.09	-0.12	-0.05	-0.08	-0.05	-0.08	-0.22	-0.22	0.03	1.00	0.53	0.72
D7	-0.55	-0.60	0.06	-0.12	-0.12	-0.12	-0.12	-0.07	-0.07	0.01	0.07	-0.02	0.03	-0.02	0.03	-0.18	-0.11	-0.01	0.53	1.00	0.30
D8	0.05	0.02	0.07	0.13	0.13	0.13	0.13	0.20	0.19	-0.02	-0.01	-0.13	-0.18	-0.13	-0.18	-0.20	-0.20	0.05	0.72	0.30	1.00
D9	-0.03	-0.04	0.03	-0.01	-0.01	-0.01	-0.01	0.03	0.03	0.10	0.13	-0.10	-0.01	-0.10	-0.01	-0.14	-0.12	-0.06	0.25	0.56	0.51
PR1	0.15	-0.03	-0.02	0.14	0.14	0.14	0.14	0.14	0.14	-0.19	-0.01	-0.11	-0.01	-0.11	-0.01	-0.16	-0.03	0.38	-0.05	0.02	0.02
PR2	0.15	-0.03	-0.02	0.15	0.15	0.15	0.15	0.15	0.15	-0.06	-0.01	0.14	-0.01	0.14	-0.01	0.01	-0.03	0.38	0.11	0.02	0.15
PR3	0.02	0.02	0.21	0.15	-0.03	-0.02	0.15	0.15	0.15	0.15	0.15	0.15	-0.09	-0.01	0.08	-0.01	-0.11	-0.03	-0.04	-0.03	0.38
PR4	0.02	0.02	0.09	0.15	-0.03	-0.02	0.14	0.14	0.14	0.14	0.14	0.14	-0.06	-0.01	0.15	-0.01	-0.08	-0.03	0.04	-0.03	0.38
PR5	0.14	-0.04	-0.02	0.15	0.15	0.15	0.15	0.15	0.15	-0.39	0.00	-0.33	-0.01	-0.33	-0.01	-0.43	-0.03	0.38	0.30	0.02	0.15
PR6	0.03	-0.01	-0.19	0.03	0.02	0.03	0.02	0.06	0.05	-0.05	0.02	0.03	-0.04	0.03	-0.04	-0.13	-0.12	0.01	0.17	-0.04	0.19
PR7	0.14	-0.04	-0.02	0.15	0.15	0.15	0.15	0.15	0.15	0.06	0.00	-0.11	-0.01	-0.11	-0.01	0.00	-0.03	0.38	0.00	0.02	-0.05
A1	-0.01	0.02	-0.03	-0.14	-0.14	-0.14	-0.14	-0.13	-0.14	0.32	-0.01	0.10	0.00	0.10	0.00	0.51	0.00	-0.47	-0.24	-0.01	-0.25
A2	0.10	0.15	-0.01	0.00	0.00	0.00	0.00	-0.02	-0.02	0.04	-0.02	0.03	-0.01	0.03	-0.01	-0.03	-0.03	-0.47	-0.14	-0.08	-0.17
A3	0.04	0.07	-0.03	-0.07	-0.07	-0.07	-0.07	-0.06	-0.06	-0.11	-0.05	-0.04	0.00	-0.04	0.00	-0.16	-0.05	-0.46	-0.07	-0.03	-0.08
A5	0.22	-0.05	-0.08	0.18	0.18	0.18	0.18	0.20	0.20	-0.10	0.11	-0.05	-0.05	-0.05	-0.05	-0.05	-0.02	-0.02	0.00	0.09	0.00
A6	-0.01	0.08	-0.02	-0.05	-0.06	-0.05	-0.06	-0.06	-0.06	0.05	-0.05	0.19	0.10	0.19	0.10	0.03	-0.14	0.02	0.00	0.06	-0.09
A7	-0.03	0.00	0.00	0.07	0.07	0.07	0.07	0.08	0.08	-0.28	-0.11	0.00	0.01	0.00	0.01	-0.11	-0.08	-0.07	-0.03	-0.01	-0.05
Q1	-0.02	0.09	-0.04	0.10	0.10	0.10	0.10	-0.16	-0.17	-0.09	0.05	0.09	0.04	0.09	0.04	-0.11	0.02	-0.03	-0.39	-0.17	-0.30
Q4	-0.13	-0.18	0.14	0.00	0.01	0.00	0.01	0.03	0.04	0.07	0.14	0.04	-0.01	0.04	-0.01	-0.14	-0.11	-0.08	0.29	0.25	0.42
Q5	0.14	0.22	-0.02	0.23	0.23	0.23	0.23	0.15	0.15	-0.01	-0.03	0.08	-0.02	0.08	-0.02	-0.03	-0.03	-0.31	-0.49	0.01	-0.38

Appendix: Correlation Matrix – Table 5

	D5	D6	D7	D8	D9	PR1	PR2	PR3	PR4	PR5	PR6	PR7	A1	A2	A3	A5	A6	A7	Q1	Q4	Q5
G1	0.05	-0.02	0.03	0.05	0.05	0.04	0.58	0.47	0.48	-0.15	-0.05	0.20	0.22	0.11	0.05	-0.24	0.01	-0.07	-0.05	0.22	0.13
G2	-0.08	-0.02	-0.02	-0.09	-0.08	0.29	0.35	0.35	0.27	0.01	-0.17	0.07	-0.27	-0.13	-0.09	-0.13	-0.05	-0.10	-0.03	-0.14	0.05
G3	-0.11	-0.06	-0.04	-0.15	-0.11	-0.01	0.11	0.10	0.03	0.38	0.20	0.17	-0.18	-0.05	-0.05	-0.16	-0.11	-0.10	-0.12	-0.20	0.00
G4	0.00	0.02	0.02	0.02	0.00	0.07	0.47	0.39	0.37	0.08	-0.32	0.17	-0.19	-0.09	-0.05	-0.12	0.12	-0.11	-0.11	0.04	-0.05
G5	-0.03	0.02	-0.01	0.02	-0.03	0.03	0.58	0.47	0.44	0.14	-0.02	0.19	-0.07	-0.07	-0.01	-0.08	0.03	-0.21	-0.12	-0.33	-0.03
G6	0.03	-0.02	0.02	0.01	0.03	-0.03	0.40	0.30	0.41	0.07	-0.01	0.04	0.57	0.32	0.58	-0.17	0.08	-0.10	0.02	0.20	0.12
G7	-0.01	0.06	0.00	0.12	-0.01	0.10	0.63	0.54	0.48	0.14	-0.03	0.17	-0.09	-0.04	-0.03	-0.09	0.03	-0.17	-0.10	0.04	0.00
G8	-0.01	-0.03	-0.02	0.02	-0.01	-0.01	0.44	0.36	0.32	0.23	0.11	0.22	-0.10	-0.07	-0.04	-0.05	0.02	-0.17	-0.11	-0.40	0.05
G9	0.22	0.10	0.12	0.26	0.22	0.00	0.06	0.01	0.09	-0.13	0.01	-0.10	0.11	0.16	0.10	0.00	0.01	0.39	0.13	-0.28	0.28
G10	0.07	0.01	0.04	0.00	0.07	0.05	-0.25	-0.18	-0.21	-0.01	-0.01	-0.14	0.11	0.10	0.04	0.04	-0.23	-0.02	0.12	-0.14	0.11
G11	0.22	0.09	0.11	0.26	0.22	0.00	0.05	0.02	0.09	-0.13	0.02	-0.09	0.22	0.20	0.21	0.00	0.02	0.43	0.20	0.15	0.30
G12	-0.03	-0.06	-0.05	-0.04	-0.03	0.05	-0.43	-0.32	-0.35	0.06	0.04	-0.15	0.01	-0.01	0.00	-0.06	-0.17	-0.03	0.04	0.02	0.03
S1	-0.04	-0.55	-0.04	-0.33	-0.04	0.99	0.99	0.99	0.99	1.00	-0.02	1.00	-0.02	-0.02	-0.02	-0.01	-0.06	-0.02	-0.05	-0.15	-0.02
S2	-0.05	-0.54	-0.06	-0.32	-0.05	0.97	0.97	0.97	0.97	1.00	-0.02	1.00	-0.02	-0.02	-0.02	-0.02	-0.06	-0.01	-0.05	-0.16	-0.02
P1	0.03	0.08	-0.11	0.12	0.03	0.15	0.15	0.15	0.15	0.15	0.09	0.15	-0.44	-0.37	-0.43	-0.02	-0.15	0.09	-0.05	0.23	-0.06
P2	0.02	0.10	-0.15	0.16	0.02	0.14	0.15	0.15	0.15	0.14	0.10	0.14	-0.43	-0.36	-0.42	0.00	-0.15	0.06	-0.04	0.24	-0.04
P3	0.03	0.06	0.04	0.12	0.03	0.14	0.14	0.14	0.14	0.13	0.06	0.14	-0.47	-0.43	-0.47	-0.03	-0.13	0.07	-0.02	0.19	-0.06
P4	0.00	0.09	-0.01	0.16	0.00	0.02	0.02	0.02	0.02	0.02	0.17	0.02	-0.99	-0.83	-0.98	0.09	0.04	-0.01	0.04	0.15	-0.04
P5	0.00	0.07	-0.01	0.14	0.00	0.02	0.02	0.02	0.02	0.02	0.17	0.02	-0.99	-0.83	-0.98	0.17	0.04	0.00	0.04	0.14	-0.03
P6	0.00	0.09	-0.03	0.16	0.00	0.02	0.02	0.02	0.02	0.02	0.17	0.02	-0.99	-0.83	-0.97	0.09	0.04	-0.02	0.04	0.15	-0.04
L1	-0.02	0.05	-0.56	0.06	-0.02	0.09	0.21	0.21	0.09	0.21	0.04	0.21	-0.01	0.11	0.07	0.15	-0.07	-0.01	-0.03	-0.09	0.13
L2	-0.03	0.08	-0.55	0.05	-0.03	0.15	0.15	0.15	0.15	0.14	0.03	0.14	-0.01	0.10	0.04	0.22	-0.01	-0.03	-0.02	-0.13	0.14
L3	-0.04	0.11	-0.60	0.02	-0.04	-0.03	-0.03	-0.03	-0.03	-0.04	-0.01	-0.04	0.02	0.15	0.07	-0.05	0.08	0.00	0.09	-0.18	0.22
L4	0.03	0.08	0.06	0.07	0.03	-0.02	-0.02	-0.02	-0.02	-0.02	-0.19	-0.02	-0.03	-0.01	-0.03	-0.08	-0.02	0.00	-0.04	0.14	-0.02
C1	-0.01	0.11	-0.12	0.13	-0.01	0.14	0.15	0.15	0.14	0.15	0.03	0.15	-0.14	0.00	-0.07	0.18	-0.05	0.07	0.10	0.00	0.23
C2	-0.01	0.11	-0.12	0.13	-0.01	0.14	0.15	0.15	0.14	0.15	0.02	0.15	-0.14	0.00	-0.07	0.18	-0.06	0.07	0.10	0.01	0.23
C3	-0.01	0.11	-0.12	0.13	-0.01	0.14	0.15	0.15	0.14	0.15	0.03	0.15	-0.14	0.00	-0.07	0.18	-0.05	0.07	0.10	0.00	0.23
C4	-0.01	0.11	-0.12	0.13	-0.01	0.14	0.15	0.15	0.14	0.15	0.02	0.15	-0.14	0.00	-0.07	0.18	-0.06	0.07	0.10	0.01	0.23
C5	0.03	0.20	-0.07	0.20	0.03	0.14	0.15	0.15	0.14	0.15	0.06	0.15	-0.13	-0.02	-0.06	0.20	-0.06	0.08	-0.16	0.03	0.15
C6	0.03	0.20	-0.07	0.19	0.03	0.14	0.15	0.15	0.14	0.15	0.05	0.15	-0.14	-0.02	-0.06	0.20	-0.06	0.08	-0.17	0.04	0.15
C7	0.10	-0.09	0.01	-0.02	0.10	-0.19	-0.06	-0.09	-0.06	-0.39	-0.05	0.06	0.32	0.04	-0.11	-0.10	0.05	-0.28	-0.09	0.07	-0.01
C8	0.13	-0.12	0.07	-0.01	0.13	-0.01	-0.01	-0.01	-0.01	0.00	0.02	0.00	-0.01	-0.02	-0.05	0.11	-0.05	-0.11	0.05	0.14	-0.03

Appendix: Correlation Matrix – Table 6

	D5	D6	D7	D8	D9	PR1	PR2	PR3	PR4	P 5	PR6	PR7	A1	A2	A3	A5	A6	A7	Q1	Q4	Q5
C9	-0.10	-0.05	-0.02	-0.13	-0.10	-0.11	0.14	0.08	0.15	-0.33	0.03	-0.11	0.10	0.03	-0.04	-0.05	0.19	0.00	0.09	0.04	0.08
C10	-0.01	-0.08	0.03	-0.18	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.04	-0.01	0.00	-0.01	0.00	-0.05	0.10	0.01	0.04	-0.01	-0.02
C11	-0.10	-0.05	-0.02	-0.13	-0.10	-0.11	0.14	0.08	0.15	-0.33	0.03	-0.11	0.10	0.03	-0.04	-0.05	0.19	0.00	0.09	0.04	0.08
C12	-0.01	-0.08	0.03	-0.18	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.04	-0.01	0.00	-0.01	0.00	-0.05	0.10	0.01	0.04	-0.01	-0.02
C13	-0.14	-0.22	-0.18	-0.20	-0.14	-0.16	0.01	-0.04	0.04	-0.43	-0.13	0.00	0.51	-0.03	-0.16	-0.05	0.03	-0.11	-0.11	-0.14	-0.03
C14	-0.12	-0.22	-0.11	-0.20	-0.12	-0.03	-0.03	-0.03	-0.03	-0.03	-0.12	-0.03	0.00	-0.03	-0.05	-0.02	-0.14	-0.08	0.02	-0.11	-0.03
D1	-0.06	0.03	-0.01	0.05	-0.06	0.38	0.38	0.38	0.38	0.38	0.01	0.38	-0.47	-0.47	-0.46	-0.02	0.02	-0.07	-0.03	-0.08	-0.31
D2	0.25	1.00	0.53	0.72	0.25	-0.05	0.11	0.11	0.12	0.30	0.17	0.00	-0.24	-0.14	-0.07	0.00	0.00	-0.03	-0.39	0.29	-0.49
D3	0.56	0.53	1.00	0.30	0.56	0.02	0.02	0.02	0.02	0.02	-0.04	0.02	-0.01	-0.08	-0.03	0.09	0.06	-0.01	-0.17	0.25	0.01
D4	0.51	0.72	0.30	1.00	0.51	0.02	0.15	0.13	0.16	0.15	0.19	-0.05	-0.25	-0.17	-0.08	0.00	-0.09	-0.05	-0.30	0.42	-0.38
D5	1.00	0.25	0.56	0.51	1.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.01	0.10	0.08	-0.03	-0.13	0.30	0.01
D6	0.25	1.00	0.53	0.72	0.25	-0.05	0.11	0.11	0.12	0.30	0.17	0.00	-0.24	-0.14	-0.07	0.00	0.00	-0.03	-0.39	0.29	-0.49
D7	0.56	0.53	1.00	0.30	0.56	0.02	0.02	0.02	0.02	0.02	-0.04	0.02	-0.01	-0.08	-0.03	0.09	0.06	-0.01	-0.17	0.25	0.01
D8	0.51	0.72	0.30	1.00	0.51	0.02	0.15	0.13	0.16	0.15	0.19	-0.05	-0.25	-0.17	-0.08	0.00	-0.09	-0.05	-0.30	0.42	-0.38
D9	1.00	0.25	0.56	0.51	1.00	0.00	0.00	0.00	0.00	0.00	-0.01	0.00	0.00	0.01	0.01	0.10	0.08	-0.03	-0.13	0.30	0.01
PR1	0.00	-0.05	0.02	0.02	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.02	-0.02	0.00	-0.07	-0.03	-0.07	-0.17	-0.05
PR2	0.00	0.11	0.02	0.15	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.02	-0.02	0.00	-0.08	0.44	-0.07	-0.17	-0.05
PR3	0.11	0.02	0.13	0.11	0.02	0.13	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.02	-0.02	0.32	-0.07	-0.17	-0.05
PR4	0.12	0.02	0.16	0.12	0.02	0.16	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.03	-0.02	0.35	-0.07	-0.17	-0.05
PR5	0.00	0.30	0.02	0.15	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.02	-0.02	0.00	-0.08	0.25	-0.08	-0.18	-0.05
PR6	-0.01	0.17	-0.04	0.19	-0.01	-0.03	-0.03	-0.03	-0.03	-0.03	1.00	-0.03	-0.20	-0.29	-0.22	0.00	-0.18	0.19	-0.33	0.21	-0.35
PR7	0.00	0.00	0.02	-0.05	0.00	1.00	1.00	1.00	1.00	1.00	-0.03	1.00	-0.02	-0.02	-0.02	0.00	-0.08	-0.24	-0.08	-0.18	-0.05
A1	0.00	-0.24	-0.01	-0.25	0.00	-0.02	-0.02	-0.02	-0.02	-0.02	-0.20	-0.02	1.00	0.89	0.99	0.27	-0.02	0.07	0.03	-0.12	0.14
A2	0.01	-0.14	-0.08	-0.17	0.01	-0.02	-0.02	-0.02	-0.03	-0.02	-0.29	-0.02	0.89	1.00	0.90	0.13	0.05	0.06	0.36	-0.09	0.57
A3	0.01	-0.07	-0.03	-0.08	0.01	-0.02	-0.02	-0.02	-0.02	-0.02	-0.22	-0.02	0.99	0.90	1.00	0.38	0.00	0.09	0.05	-0.09	0.17
A5	0.10	0.00	0.09	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.27	0.13	0.38	1.00	0.16	-0.04	-0.16	-0.13	-0.06
A6	0.08	0.00	0.06	-0.09	0.08	-0.07	-0.08	-0.07	-0.07	-0.08	-0.18	-0.08	-0.02	0.05	0.00	0.16	1.00	-0.07	0.10	-0.23	0.15
A7	-0.03	-0.03	-0.01	-0.05	-0.03	-0.03	0.44	0.32	0.35	0.25	0.19	-0.24	0.07	0.06	0.09	-0.04	-0.07	1.00	0.05	0.19	0.10
Q1	-0.13	-0.39	-0.17	-0.30	-0.13	-0.07	-0.07	-0.07	-0.07	-0.08	-0.33	-0.08	0.03	0.36	0.05	-0.16	0.10	0.05	1.00	-0.17	0.73
Q4	0.30	0.29	0.25	0.42	0.30	-0.17	-0.17	-0.17	-0.17	-0.18	0.21	-0.18	-0.12	-0.09	-0.09	-0.13	-0.23	0.19	-0.17	1.00	-0.11
Q5	0.01	-0.49	0.01	-0.38	0.01	-0.05	-0.05	-0.05	-0.05	-0.05	-0.35	-0.05	0.14	0.57	0.17	-0.06	0.15	0.10	0.73	-0.11	1.00

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List of Abbreviations

AMA	Advanced Measurement Approach
A/P	Accounts Payable
A/R	Accounts Receivable
BWG	Bankwesengesetz
CP3	Third Consultative Paper of Basel Committee on Banking Supervision
EAD	Exposure at Default
EDF	Expected Default Frequency
ESFRC	European Shadow Financial Regulatory Committee
EU	European Union
FCG	Financial Guardian Group
HGB	Handelsgesetzbuch
IRB	Internal ratings-based (approach)
L/C	Letter of credit
LGD	Loss Given Default
NACE	Nomenclature générale des activités economiques dans les communautés européennes
n/a	not applicable
M	Maturity
OCC	Office of the Comptroller of the Currency
QIS3	Quantitative Impact Study
PD	Probability of Default
r	Risk weight
RC	Regulatory Capital
ROA	Return on Assets
RWA	Risk-weighted assets
SD	Standard Deviation
SME	Small and Medium sized Economy
S&P	Standard & Poor´s
TNW	Tangible Net Worth