Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER'S THESIS

Regulatory Approaches to Credit Risk Quantification

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Academic Year: **2015/2016**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently; using only the listed resources and literature, and the thesis has not been used to obtain a different or the same degree.

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Prague, July 29, 2016

Signature

Acknowledgments

I am very grateful to my supervisor, Mgr. Magda Pečená Ph.D., for her willingness to consult with me, read my thesis several times and provide me always with valuable comments and suggestions.

Abstract

Credit risk represents one of the most significant risks which a bank must face, and therefore, its intention is effectively manage and measure this risk. However, management and measurement methods are supervised and influenced by national regulators. Banking regulatory supervision plays a significant role among others in determining minimum capital requirements that serve as buffer against losses stemming from credit risk. This thesis provides theoretical foundation of regulatory approaches – standardized and internal rating based (IRB) approach – used for quantification of regulatory capital to credit risk as well as empirical application of such approaches on created portfolio of corporate loans. As a part of IRB method I suggested a model composed of financial ratios estimating probability of default using logistic regression. I founded out that rather the use of combination of financial ratios from different groups of ratios with slight dominance of profitability ratios forms final model. Therefore, superiority of solvency ratios in modelling cannot be proved on my portfolio. After estimating and determining necessary parameters I quantified the minimum regulatory capital requirements to credit risk under standardized and IRB approaches prescribed by Basel III. In the end, the results are compared with conclusion that more risk sensitive approach is favorable in terms of less required capital for selected portfolio of corporates.

JEL Classification	G21, G28, C13
Keywords	capital, credit risk, regulation, external rating, internal rating system, capital adequacy

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Abstrakt

Kreditní riziko představuje jedno z nejvýznamnějších rizik, kterému banka musí čelit, a tudíž je v jejím zájmu ho efektivně řídit a měřit. Nicméně metody řízení a měření jsou dozorovány a ovlivňovány národními regulátory. Bankovní regulatorní dohled hraje důležitou roli mimo jiné i ve stanovování minimálních kapitálových požadavků, které slouží jako polštář pohlcující ztráty pramenící z kreditního rizika. Tato práce pojednává o regulatorních přístupech využívaných ke kvantifikaci kapitálových požadavků ke kreditnímu riziku – standardizovaný přístup a přístup založený na interních ratinzích (IRB) – z hlediska teoretického a zároveň poskytuje empirickou aplikaci těchto přístupů na náhodně vytvořeném portfoliu korporátních půjček. V rámci metody IRB jsem navrhla model založený na finančních ukazatelích, který aplikuje logistickou regresi k odhadnutí pravděpodobností selhání. Na základě modelování jsem došla k závěru, že pro finální model je lepší raději využít kombinaci finančních ukazatelů z různých skupin s mírnou dominancí ukazatelů rentability a tudíž jsem nemohla potvrdit hypotézu, že ukazatelé solventnosti jsou při modelování pravděpodobnosti selhání nadřazení ostatním ukazatelům. Po získání potřebných parametrů jsem kvantifikovala minimální kapitálové požadavky ke kreditnímu riziku využitím jak standardizovaného tak i IRB přístupu podle Baslu III. Na základě výstupů obou metod jsem došla k závěru, že více rizikově citlivý přístup je příznivější z hlediska menších kapitálových požadavků pro zvolené portfolio korporací.

Klasifikace	G21, G28, C13
Klíčová slova	kapitál, kreditní riziko, regulace, externí rating, systém interních ratingů, kapitálová přiměřenost

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Contents

List of Tables

List of Figures

Acronyms

AUROC	Area under ROC curve
BCBS	Basel Committee on Banking Supervision
CET 1	Common Equity Tier 1
CR	Capital Requirements
CRA	Credit Rating Agency
CRD IV	Capital Requirements Directive IV
CRR	Capital Requirements Regulation
EAD	Exposure at Default
EBA	European Banking Authority
ECAI	External Credit Assessment Institution
EL	Expected Losses
FSB	Financial Stability Board
GICS	Global Industry Classification Standard
IRB	Internal Ratings Based Approach
LGD	Loss Given Default
M	Maturity
MDA	Multiple/Multivariate Discriminant Analysis
OLS	Ordinary Least Squares
PD	Probability of Default
ROC	Receiver Operating Characteristic
RWA	Risk Weighted Asset
S&P	Standard & Poor's
SA	Standardized Approach
UL	Unexpected Losses
VIF	Variance Inflation Factor

Master's Thesis Proposal

Author:	Bc. Pavla Stará
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Defense Planned:	June 2016

Proposed Topic:

Regulatory approaches to credit risk quantification

Motivation:

Nowadays is the necessity to keep sufficient amount of capital more than obvious. Not only recent global financial crisis in 2008 is a very good example why are capital requirements and risk management as a whole in a big focus of financial institutions as well as regulatory organs. For instance, collapse of one of the biggest U.S. investment banks that time – Lehmann Brothers – represents an unforgettable event in a history of global financial markets.

Financial institutions can come up with their own approaches how to set capital requirements. So why do we have a regulation here? There are concerns about the fact that companies may not have an incentive to keep a sufficient amount of capital as they can exploit the money e.g. with the intention to create profits from risky businesses. Therefore, the regulatory organ known as a Basel Committee on Banking Supervision (BCBS) presents its actual Basel Capital Accord known also as Basel III. Capital requirements should serve as a buffer against unexpected losses, which can occur with a very small probability but when it happens, the consequences can be devastating. Therefore, an important question arises – Can the existing approaches to capital requirements work also in turbulent periods or are they sufficient only for quiet periods? Peng (2009) is one of the researches who investigates risk measuring techniques under uncertain environment.

The proposition of Basel regulatory framework has evoked researchers to investigate what impacts has the capital requirement on banking behaviour. Such an issue examined already in 1999 Jackson when she reviewed the empirical evidence on the impact of 1988 Basel Accord. Further studies such as Gual (2011) or Awdeh *et al*. (2011) studied the influence of higher capital requirements proposed in Basel III on banks' risk-taking behavior with conclusion that increased capital requirement are rather unlikely to shrink this risk-taking attitude.

Hypotheses:

1. Using more sophisticated regulatory models banks reach lower capital requirements.
2. Solvency ratios are superior to other groups of financial ratios in the bankruptcy prediction.

Methodology:

I will create my own portfolio of corporate clients. The data of these clients will be obtained mainly from database Factset. I will apply to this portfolio regulatory approaches to capital requirements for credit risk proposed by Basel III. I will present a Standardized approach, where ratings are used from external rating agencies, further, foundation Internal Ratings Based approach (FIRB), where we have now own Probability of Default (PD) estimates and other parameters necessary for calculation are prescribed by regulator, and as a last advanced IRB approach, where we use our own estimates for all parameters. The derivation of capital requirements will be based on first two approaches. In the Standardized approach I will employ issuer ratings provided by Standard & Poor's. Regarding the FIRB and the development of the default prediction model and therefore, an estimation of PD I will use an accounting-based model and will apply among literature widely used logistic regression. Necessary regressions, estimations and calculations will be performed in statistical software R and MS Excel. The results from both methods, SA and FIRB, will be compared and discussed with the aim to support stated hypothesis.

Expected Contribution:

Banks face many risks and credit risk is one of the most important one. Therefore, a main purpose of my Master Thesis is to provide a deeper look at possible credit risk management approaches as banks do not openly share such information due to high sensitivity of the data.

Outline:

1.Introduction
2.Literature review
3.Banking regulatory supervision
4.Data
5.Standardized approach
6.Internal ratings based approach
6.Comparison and discussion of the results

Core Bibliography:

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Author **Supervisor**

1 Introduction

Capital represents an indispensable item on banks' balance sheet not only because it serves as a loss absorber in bad times. When a bank suffers sharp losses stemming from unexpected fall in value of bank's assets, holding a sufficient level of capital enables the bank to continue with fulfilment of its obligations such as funding withdrawals and therefore, to avoid being insolvent. A good example that an entity without adequate capital could go bankrupt or be on verge of collapse provides us the global financial crisis in 2008 when even some large financial institutions (such as Lehman Brothers) filed for bankruptcy.

The influence of regulatory organs on the adequate level of capital is more than obvious. Already for decades the regulator Basel Committee on Banking Supervision has issued recommendations regarding not only holding the sufficient level of capital known as minimum capital requirements that have been accepted by substantial number of countries around the world. Under the Basel III that is the most up-to-date version of regulatory framework so far the overall minimum capital requirement is the sum of capital requirements for credit, market and operational risk.

The global financial crisis in 2008 was a trigger of re-examination of current regulatory rules. In 2010 the new Basel Accord – Basel III was released setting a higher capital requirements and presenting a new global liquidity framework. The re-examination has brought the increase in both quantity and quality of the regulatory capital base and improved the risk coverage of the capital framework.

Credit risk that has been part of overall regulatory capital requirement since Basel I is one of the main risks to which financial institution must face on everyday basis when conducting business. Hence, on its measurement and management banks put great emphasis. But banks do openly share neither their risk management techniques nor the background data as these are highly sensitive information. Therefore, I decided to collect my own sample data and apply two regulatory methods that banks may use to quantify minimum capital requirements to credit risk according to prescribed Basel rules – Standardised Approach (SA) and Internal Ratings Based (IRB) Approach. The

thesis should thus provide a deeper look into possible regulatory credit risk management techniques.

Next to the simulation of determination of regulatory capital requirements to credit risk I will try to prove empirically the hypotheses that using more sophisticated regulatory models banks reach lower capital requirements.

The main difference between SA and IRB methods stems from the possibility to include internal modelling in case of IRB into the calculation. SA is based on obligors' assessment provided from external rating agencies. Hence, the method does not allow to incorporate any internal models. Whereas IRB approach allows internal modelling of inputs necessary for the prescribed capital requirements formula. The regulatory framework offers two IRB techniques – foundation and advanced. In the thesis I will use for the simulation purposes the foundation IRB since I haven't retrieved necessary data for the advanced IRB method. The foundation approach is based on the modelling of probability of default while the other parameters are set by the regulator.

Probability of default estimation is a widely studied issue as it is an important fact for a bank or financial institution in a decision process whether to provide a loan or not to a potential obligor. The researches have come up with various approaches to credit risk modelling and getting default probabilities such as accounting-based models or structural models. Due to data availability the modelling approach in this thesis employs accounting-based model.

Between seminal studies in a history of investigating bankruptcy prediction using accounting information belong Altman (1968) and Ohlson (1980). Both studies have developed models to predict bankruptcy. The first study uses a multiple discriminant analysis while the second one applies logistic regression that will be employed also in this thesis. Nevertheless, I will not use parameters for the probability of default modelling prescribed directly by such already developed model, but I would rather apply the selection process to get from set of financial ratios the variables suitable for my final model. Based on that I would like to investigate the hypothesis whether solvency ratios are superior to other financial ratios in bankruptcy prediction modelling.

The outline of the thesis is as follows. The next chapter provides a review of previous studies related to Basel framework as well as reviews the research focused on default prediction. Chapter 3 outlines the development of Basel regulatory framework and takes a deeper look on what new Basel III brings regarding the regulatory capital requirements. Following section presents the possible regulatory approaches to credit risk and simultaneously describes the created portfolio to which the capital requirement will be determined. Chapter 5 is devoted to a detailed analysis of the Standardised Approach. Next to that the section focuses also on the description of the steps necessary to determine the capital requirements as well as provides result of this method. The following chapter analyses the second method – IRB approach. First, the theoretical review of this technique is presented. Further, the chapter focuses on the probability of default that is modelled in this thesis as the parameter entering the regulatory formula. Within the scope of this chapter the variable selection procedure is suggested followed by the design of PD model that is in the end evaluated by two selected techniques – classification matrix and receiver operating characteristic. After I get desired PDs I set an internal rating system based on regression model. Moreover, I propose another internal rating system that is derived from Standard & Poor's transition matrix. I also determine based on regulatory rules the rest of the parameters necessary for the regulatory formula and quantify capital requirements to credit risk first using PDs from model internal rating system and then using PDs from S&P's internal rating system. The last chapter compares the outputs of both regulatory approaches and discusses the hypothesis about more sophisticated regulatory models.

2 Literature Review

2.1 Basel regulation

Creation of Basel regulation has woken up interest among the researchers. Beside others, the literature has focused on the analysis of the link between regulatory capital requirements and banking risk. Gual (2011) provides empirical and theoretical arguments behind the higher level of required capital suggested by Basel III. The study proposes that new capital regulations are rather unlikely to reduce bank risk-taking whereas higher level of capital requirements may probably increase the costs of fund in the banking environment with severe impacts on the real economy. Further, Ugwuanyi (2015) investigated in her study the influence of the regulation of minimum capital requirements on a bank's risk-taking behaviour. She founded out that enhanced regulation induce the decrease in bank's risk-taking appetite. Despite the existence of negative correlation between regulatory requirements and risk-taking behaviour of the bank the impact is not statistically significant. Ugwuanyi's finding is in accordance with a study of Rime (2001) who using the simultaneous equation model concluded that the regulatory pressure causes an increase in bank's capital but has no effect on the level of risk taken by banks in Switzerland. Moreover, Rime (2001) found out that the effect of availability of higher level of capital and decreased risk-taking behaviour clearly leads to lower bank's default probability. Risk-taking appetite was also analysed by Awdeh *et al*. (2011). They investigated it also with the use of simultaneous equation model on a panel data of commercial banks in Lebanon and founded out that increase in bank risk is a consequence of higher capital requirements. Their study further suggests that Lebanese banks depend more on retained earnings in meeting required capital level since they found the positive relationship between growth in capital and bank profitability. In the end, Awdeh *et al*. (2011) indicated that larger banks have a tendency to keep lower level of capital and control risk better through diversification.

2.2 Default prediction modelling

Banks that want to compute their minimum capital requirements according to Internal Ratings Based approach (IRB) need to develop models to estimate the parameters used in the formula. This thesis will simulate the calculation of capital requirements with

the use of foundation IRB method. It means that the modelling of Probability of Default will be performed. Accounting based models that a risk management in a bank can use as an assessment tool have their roots already in the first half of the 20th century. The issue of the predictive power of various financial ratios was addressed for the first time by Fitzpatrick in 1932. He conducted his study on a portfolio of 40 companies of which half is presented by failed ones and the other half is presented by surviving ones. The companies were matched by factors consisting of size, industry and date (so called pair-matched portfolio). On the one hand, Fitzpatrick (1932) did not perform statistical analysis. On the other hand, he focused on the analysis of the ratios and their trends and employed simple multivariate analysis. Beaver (1966) came up with a study applying univariate analysis based also on the pair-matched portfolio on which he evaluated the predictive ability of different financial ratios by using t-tests. As a milestone in a research literature focusing on financial ratios and their bankruptcy prediction ability is considered to be a study conducted by Altman (1968). He performed a multiple discriminant analysis instead of univariate analysis on also pair-matched portfolio. As the predictors of company's failure Altman (1968) utilised five financial ratios that gave birth to the well-known Z-score. His research is very accurate in its prediction whether the companies are going to bankrupt or not over a one year horizon.

Another milestone in the literature that investigates the topic of using financial ratios to predict financial failure is considered to be Ohlson's (1980) paper. He came up with a significant methodological changes in the field of bankruptcy prediction. Namely, Ohlson (1980) applied logistic regression instead of multiple discriminant analysis on a much larger sample portfolio that was not pair-matched. He successfully developed so called O-score together with four statistically significant factors that predicts the probability of default. These are measures of financial structure, measures of current liquidity, measures of performance, and the size of the firm. It appears that Ohlson's (1980) research has laid the foundation for a lot of later studies in the area of the predictive power of financial ratios. We can find the references to this paper in many later studies from this field.

The Altman's Z-score and the Ohlson's O-score led the later researchers to determine the bankruptcy estimates with the use of those scores. Aloy Niresh & Pratheepan

(2015) study examines the trading sector in Sri Lanka by the application of Altman's Z-score. The research aimed on the classification of the companies in different levels of financial position – safe, grey and distress. The finding that 71 % of firms is classified as financially distressed and the rest of 29 % belongs to the grey zone indicates that the trading sector as a whole is in threat. Hayes *et al*. (2010) employed an alternative Z''-score (Altman & Hotchkiss, 2006) modified to non-manufacturing firms. In the estimation of financial distress for a portfolio of retail companies they reached 94 % model accuracy. Further, Ugurlu & Aksoy (2006) followed statistical techniques from Altman (1968) as well as Ohlson (1980) and developed models for predicting corporate financial distress in the environment of emerging market in Turkey. The study concluded that the logit model performs better – higher classification power and predictive accuracy – than the discriminant model in such an environment.

The studies that focused their attention on development of bankruptcy prediction model for a particular industry have also their place in the literature. Diakomihalis (2012) employed in his study three version of Altman Z-score to examine the bankruptcy predictions in hotel industry in Greece. He found out that the original Z-score (Altman, 1968) formula provides the most precise estimates of model accuracy – 88.2 % one year prior bankruptcy in comparison with other two models. Therefore, the researcher concluded that Altman's Z-score can be utilised with substantial success for bankruptcy forecasting. Retail industry was investigated, for instance, by Hayes *et al*. (2010) or Keener (2013). Keener (2013) confirms the hypothesis that smaller retail companies with fewer employees are more likely to default. Further, Makeeva & Neretina (2013) predicts bankruptcy in construction industry. Kim & Gu (2006) investigate bankruptcy in restaurant industry. Aloy Niresh & Pratheepan, (2015) focus their study on trading sector and Ray (2011) investigates the corporate financial distress in the glass and glassware industry.

The accounting based bankruptcy prediction models are also commonly developed for countries throughout the world. Low *et al.* (2001) attempt to predict financial distress in Malaysia. Pervan *et al*. (2011), Diakomihalis (2012), and Makeeva & Neretina (2013) all focus on prediction of company bankruptcy in various countries in Europe. Financial distress in India investigates Ray (2011). Ugurlu & Aksoy (2006) examined

financial distress in an emerging market of Turkey. Chava & Jarrow (2004), Kim & Gu (2006) as well as Keener (2013) developed bankruptcy prediction model for the firms in the United States.

Already since the Altman's study (1968) many methods have emerged among the research literature focused on the prediction of corporate financial distress. As stated by Kumar & Ravi (2007) the techniques employed to analyse corporate credit risk can be split into two main groups: statistical techniques and artificial intelligence techniques. Despite the huge number of studies undertaken in this field a lingering interest showed by practitioners and academics only proves how important the appropriate managing of credit risk is also in the present times.

Between the most widespread statistical methods belongs, for instance, a discriminant analysis (Pervan *et al*., 2011), probit model (Lennox, 1999), and the logit model (Keener, 2013) that will be employed in this thesis. Many approaches have been developed within the group of artificial intelligence techniques such as neural networks (Iturriaga & Sanz, 2015), decision trees (Zheng & Yanhui, 2007), genetic algorithms (Kim & Kang, 2012) and support vector machines (Kim *et al*., 2005) that belong between common ones from this area.

3 Banking Regulatory Supervision

3.1 Basel Accord development

Roots of a regulatory organ Basel Committee on Banking Supervision (BCBS) date back to the year 1973. In 1988 BCBS issued its first Basel Accord as the beginning of the convergence of somewhat different approaches that countries adopted. Main focus of Basel I was concentrated on credit risk as the most important risk source across the banking sector. Nevertheless, this quite rough regulatory approach with risk measurement in an insufficiently differentiated way needed to be revised. (McNeil *et al.*, 2015)

Under the pressure of highly dynamic world development of regulatory framework was more than necessary. In 1996 BCBS introduced an important amendment to Basel I consisting of standardised model for market risk and moreover the permission for bigger banks to choose an internal Value-at-Risk-based model for that risk. But the problems mainly with credit risk still persisted; therefore, the regulatory organ came up with a new version of Basel Accord – Basel II – firstly initiated in 2006. Basel II was based on three-pillar system of regulation. Pillar 1 deals with a regulatory capital and its measurement; Pillar 2 is formed by modelling process overview, containing risks not considered in Pillar 1; and the last Pillar 3 states a comprehensive set of disclosure requests. New regulation puts emphasis on more risk-sensitive approach to evaluate the risk of banks' credit portfolios. Several amendments and additions to the content of the initial version of Basel II were applied. Nevertheless, in 2007-9 the global financial crises emerged and revealed the procyclicality effects of Basel II capital requirements. In 2009 BCBS proposed some improvements to Basel II known as Basel 2.5. (McNeil *et al*., 2015)

The latest version so far, so called Basel III, was agreed in 2010 with a gradual implementation since 2013. The aim of the enhanced version Basel III was to revise and strengthen the three pillars system presented in Basel II as well as extend the regulatory framework with several innovations related to capital conservation buffer, countercyclical capital buffer, leverage ratio, liquidity requirements and additional

proposals for systematically important banks. (BIS, 2015) Following *Table 3-1* illustrates the timeline of Basel III phase-in arrangements.

Table 3-1

Basel III phase-in arrangements

	Phases	2013	2014	2015	2016	2017	2018	2019
Capital	Leverage Ratio		Parallel run 1 Jan 2013 – 1 Jan 2017 Disclosure starts 1 Jan 2015				Migration to Pillar 1	
	Minimum Common Equity Capital Ratio	3.5%	4.0%	4.5%				4.5%
	Capital Conservation Buffer				0.625%	1.25%	1.875%	2.5%
	Minimum common equity plus capital conservation buffer	3.5%	4.0%	4.5%	5.125%	5.75%	6.375%	7.0%
	Phase-in of deductions from CET1*		20%	40%	60%	80%	100%	100%
	Minimum Tier 1 Capital	4.5%	5.5%	6.0%				6.0%
	Minimum Total Capital				8.0%			8.0%
	Minimum Total Capital plus conservation buffer		8.0%		8.625%	9.25%	9.875%	10.5%
	Capital instruments that no longer qualify as non-core Tier 1 capital or Tier 2 capital		Phased out over 10 year horizon beginning 2013					
Liquidity	Liquidity coverage ratio – minimum requirement			60%	70%	80%	90%	100%
	Net stable funding ratio						Introduce minimum standard	

* Including amounts exceeding the limit for deferred tax assets (DTAs), mortgage servicing rights (MSRs) and financials.

-.-.-transition periods

Source: Basel III, 2011

Necessity of transposing the Basel agreements – Basel III – into the European law led to an implementation of directive known as the Capital Requirements Directive "CRD IV" and regulation known as the Capital Requirements Regulation "CRR". These documents reflect Basel regulatory framework. Moreover, they have a wider scope than Basel III as CRD IV and CRR take into account not only credit institutions but also investment companies. European Banking Authority (EBA) plays a significant role in the implementation process of Basel Accord into the European law. CRR serves as a legally binding regulation that is directly applicable in all member states. On the contrary, CRD IV first need to be transposed into member states' discretion in a way appropriate to their respective environment. The scope of CRD IV summarizes the following *Figure* 3-*1*. I will focus my attention mainly towards section Capital requirements in this thesis.

Figure 3-1

CRD IV framework		
Capital requirements	Leverage ratio	Liquidity rules
Supervisory review	Disclousure	Large exposure

Source: CRD IV, 2013

The new regulatory rules' impact has been monitored since 2010 on semi-annual basis by the BCBS at a global level and by the European Banking Authority at European level (EBA, 2015). The European Union's revised framework for bank capital requirements became effective on 1 January 2014 and all banks operating in the EU are obliged to follow the regulatory rules. Despite of previous period when a system of regulatory requirements was implemented through member state laws and regulations, now it has been largely substituted by comprehensive requirements which are meant to apply directly and uniformly among the EU member states. Nevertheless, this approach is challenging for the European Union in that there is necessary to take into account the diversity of individual institutions in different member states that can be very small local ones on the one hand, and on the other hand, specialised banks or even the largest global systematically important banks. The CRR and the CRD IV try to comply with individual EU member states' various banking systems and financial markets that are at different stages of development by rendering alternative approaches to the calculation of capital requirements not only for credit risk including different levels of risk-sensitivity and requiring various levels of sophistication (CRR, 2013). An ongoing monitoring of gradual implementation of regulatory requirements conducted by EBA is based on data provided by participating banks on voluntary and confidential basis (EBA, 2015).

3.2 The Basel III capital requirements

Risk-based capital requirements are considered to create a sufficient amount of capital to cover unexpected losses. Nevertheless, the recent global financial crisis proved insufficiency of these requirements to prevent banks having too high leverage risk. (CRR, 2013) We should take into consideration that Basel Accord is a basic regulatory framework that serves as a recommendation. But nowadays, the framework is widely

accepted by the countries that implement it in their national laws. For instance, the Czech Republic issued "*Decree No. 163/2014 Coll., on the performance of the activity of banks, credit unions and investment firms*", that processes the European Union Directive 2013/36 (CRD) as well as builds on directly applicable European Union Regulation No 575/2013 (CRR). CRD and CRR are direct transformation of Basel regulation. Nevertheless, this thesis is focused neither on a specific member state nor on a specific area such as EU. Therefore, there are mainly mentioned the rules and definitions set in Basel III.

The necessity to enhance the resilience of the banking sector brought the Basel Committee to the idea of reinforcing the regulatory capital framework. The idea has built on the system of three pillars presented already in Basel II where pillar 1 deals with minimum regulatory capital requirements based on risk weighted assets (RWA) incorporating credit, market, and operational risk, pillar 2 focuses on risk management and supervision, and the final pillar 3 aims on improving the disclosures on the individual elements of regulatory capital and their reconciliation to the reported accounts so that the banks will be more transparent. (BIS, 2011) In this section I will briefly discuss the scope of the risk-based regulatory capital of institutions that is presented in Basel III.

3.2.1 Capital definition

Regarding the capital definition, revised regulatory framework renders several changes in comparison with Basel II. Important point is the much stricter definition of capital with an emphasis on better capital quality representing higher loss-absorbing capacity. When we take a look at individual elements of capital, part called Tier 3 completely vanished from revised regulation as a capital component originally reserved to cover market risks. Elements Tier 1 and Tier 2 are still in place in Basel III but now with obvious purpose of strengthening Tier 1. Tier 1 consist of common equity Tier 1 and additional Tier 1. As per reserved limits, proportion of common equity Tier 1 must be equal or above the level of 4.5 % RWA, while under Basel II was required to hold 2 % RWA; total Tier 1 capital must be equal or above the level of 6 % RWA in comparison to Basel II where the stipulated level was 4 %; and finally the sum of Tier 1 and Tier 2 must not breach the 8 % level. (Basel III, 2011)

As stated in Basel III, common equity Tier 1 consists of following items (BIS, 2011):

- *"Common shares issued by the bank that meet the criteria for classification as common shares for regulatory purposes;*
- *Stock surplus (share premium) resulting from the issue of instruments included Common Equity Tier 1;*
- *Retained earnings;*
- *Accumulated other comprehensive income and other disclosed reserves;*
- *Common shares issued by consolidated subsidiaries of the bank and held by third parties (i.e. minority interest); and*
- *Regulatory adjustments applied in the calculation of Common Equity Tier 1."*

Calculations and related rules to listed items are out of scope of this work. For detailed information please refer to Basel III document.

Regarding components of additional Tier 1, BIS (2011) mentions:

- *"Instruments issued by the bank that meet the criteria for inclusion in Additional Tier 1 capital (and are not included in Common Equity Tier 1);*
- *Stock surplus (share premium) resulting from the issue of instruments included in Additional Tier 1 capital;*
- *Instruments issued by consolidated subsidiaries of the bank and held by third parties that meet the criteria for inclusion in Additional Tier 1 capital and are not included in Common Equity Tier 1; and*
- *Regulatory adjustments applied in the calculation of Additional Tier 1 Capital."*

And the last component from definition of capital Tier 2 is defined in BIS (2011) as follows:

- *"Instruments issued by the bank that meet the criteria for inclusion in Tier 2 capital (and are not included in Tier 1 capital);*
- *Stock surplus (share premium) resulting from the issue of instruments included in Tier 2 capital;*

- *Instruments issued by consolidated subsidiaries of the bank and held by third parties that meet the criteria for inclusion in Tier 2 capital and are not included in Tier 1 capital;*
- *Certain loan loss provisions; and*
- *Regulatory adjustments applied in the calculation of Tier 2 Capital."*

It can seem that provided lists of items of individual capital elements are quite general and vague. Actually, the capital definition is more exact in comparison to Basel II.[1] Moreover, we have to take into account that regulatory capital has to be modified when applicable using several regulatory adjustments such as deduction of goodwill and other intangible assets as well as of deferred tax asset from Common Equity Tier 1, for instance. (BIS, 2011)

There is an obvious change in perception of equity in comparison to the original regulatory framework Basel II. The differences in capital definition stemming from the tightening of rules related to individual capital elements are the reaction on global financial crisis.

3.2.2 Capital requirements

One of the sources of Basel II weaknesses that surfaced during the 2008 global financial crisis was inconsistent definition of capital among jurisdictions as the BCBS itself admits. This together with narrow information disclosure precluded markets from evaluation and comparison of quality of bank capital. (BIS, 2011) Between major aims proposed already in consultative document in 2009 over earlier Basel I and Basel II belong following objectives (BCBS, 2009):

- *"dampen any excess cyclicality of the minimum capital requirement;*
- *promote more forward looking provisions;*
- *conserve capital to build buffers at individual banks and the banking sector that can be used in stress; and*
- *achieve the broader macroprudential goal of protecting the banking sector from periods of excess credit growth*."

[1] For detail information on individual capital components and conditions that have to these components comply please refer to BIS (2011).

The last two points are the base for two newly suggested capital buffers known as capital conservation buffer and countercyclical capital buffer (Repullo & Saurina, 2011).

The banks will be required to hold capital conservation buffer at a level of 2.5 % of RWA. The creation of this type of capital can start after the common equity Tier 1 satisfies the minimum capital requirements. Afterwards, the rest can be added to the conservation buffer. (Basel III, 2011) Its phasing in should start at 0.625 % in 2016 and it should gradually end up at 2.5 % in 2019. The reason behind requesting the banks to build up the conservation buffer is to secure maintaining a cushion of sufficient capital which can be exploited to mitigate losses during periods of economic and financial stress. In other words, creating conservation buffer should lead to more resilient banking sector going into downturn as well as during the economic recovery to provide the mechanism for rebuilding the capital. The sources for this cushion should stem from bank's own resources such as restriction of paid out dividends, payments of employee bonuses and repurchasing of their own shares. Another possible way how to contribute to conservation buffer is to acquire capital from private sources. (Kubat, 2014) The elements entering into the capital cushion are part of common equity Tier 1 according to its definition in Basel III. As it was already mentioned, after the complete implementation capital conservation buffer should reach the level of 2.5 % RWA and common equity Tier 1 4.5 % RWA. It implies the final amount of common equity Tier 1 (CET 1) ratio will be 7 % RWA. When the bank will not be able to meet these requirements it will have to accept some solutions for the situation. The *Table 3-2* presents the scenarios what happens in case when a bank will not meet the desired level of 2.5 % RWA for conservation buffer but 4.5 % level for common equity Tier 1 is satisfied. The imposed restrictions only concern the distribution. For instance, when a bank's CET 1 ratio falls into the range 5.75 % - 6.375 % it implies the requirement to conserve 60 % of its earnings in the following year (retained earnings). In other words, the bank should not pay out more than 40 % as dividends, repurchased shares, and payments of employee bonuses.

Table 3-2

Individual bank minimum capital conservation standards

Common Equity Tier 1 Ratio	*Minimum Capital Conservation Ratios (expressed as a percentage of earnings)*
4.5% - 5.125%	100%
>5.125% - 5.75%	80%
>5.75% - 6.375%	60%
>6.375% - 7.0%	40%
> 7.0%	0%

Source: BIS, 2011

Deepening of financial crisis through the pro-cyclical reinforcing of financial shocks not only across the banking sector but also financial markets and the real economy led Basel Committee to come up with approaches how to mitigate the pro-cyclical dynamics. BCBS imposes countercyclical capital buffer to vary minimum capital requirements throughout the economic cycle (i.e. pro-cyclical capital requirements). (Jiménez *et al*., 2012) Nevertheless, this kind of financial cushion is a voluntary element of national regulators as the Committee believes that national regulators are the one who should be able to inhibit excessive credit expansion. (Kubat, 2014) As part of the cyclical requirements of macroprudential policy the principal lies in rising capital requirements, i.e., tightening, in good times, while shrinking the requirements, i.e., loosening, when the economy is in recession (Jiménez *et al*., 2012). Suggested size of countercyclical capital buffer ranges from 0 % to 2.5 % of risk weighted assets. Basel Committee issued in 2010 "*A guidance for national authorities operating the countercyclical capital buffer*" (BCBS [a], 2010). Calculation of the buffer is based on weighted average of particular country requirements, where the weights are considered to be the risk exposure in specific countries (Kubat, 2014). Its creation is in the principal equal as in case of capital conservation buffer. Therefore, the countercyclical cushion regarding its quality appertains also to the common equity Tier 1. When the national regulator decides to practise full extent of 2.5 % RWA for countercyclical capital buffer, it will lead to rise of common equity Tier 1 to 9.5 % of RWA (Kubat, 2014).

In general, the requirement for banks to retain the minimum total (regulatory) capital equivalent to at least 8 % of their total risk-weighted assets (inclusion of credit, market,

and operational risk) remains the same as within Basel II. Nevertheless, when combined with capital conservation buffer it should reach the level of 10.5 % RWA at the latest in 2019.

Basel III also comes up with additional capital requirements directed at systematically relevant financial institutions. Systematically relevant financial institutions are such financial institutions whose disorderly laps, because of their complexity, systemic interconnectedness, and size, would bring significant disruption across the broader financial system and economic activity (BiiiCPA, 2011). The Basel Committee in cooperation with Financial Stability Board (FSB)[2] focus on this issue of an extra loss absorbing capacity above stated standards. They together evolve for systematically relevant financial institutions a well-integrated approach that could consist of e.g. contingent capital[3] and capital surcharges[4] (BCBS [b], 2010).

The additional requirements indicate the composition of total regulatory capital for systematically important financial institutions as follows: (Tier 1 Capital Ratio) + (Countercyclical Capital Buffer) + (Capital Conservation Buffer) + (Capital for Systematically Important Banks).

[2] FSB represents international body that monitors and makes recommendations about the global financial system.

[3] Contingent capital should be used when a bank is headed toward failure. It is a source of automatic equity injection that should hold the bank out of distress. Between the sources of contingent capital that mostly consists of a debt that under specified conditions converts into equity belongs e.g. contingent convertible bonds.

[4] Systematically important financial institutions should hold additional top-quality capital against unforeseen losses.

4 Regulatory approaches to credit risk

Importance of credit risk within financial sector has been reflected by regulator in Basel Capital Accords since 1988. Continual development of various approaches to credit risk implies increasing focus on that risk. Financial institutions are provided with two approaches to credit risk in the range of regulatory framework. The simpler one stipulated within Basel III is the Standardised Approach that uses external credit ratings provided by external credit rating agencies to identify risk weights for capital charges. The Standardised Approach produces a relatively conservative estimate of capital requirements to credit risk. Institutions can also be permitted under the specified conditions and supervisory approval to apply Internal Ratings Based Approach (IRB). This approach is more sophisticated technique demanding more input data assessed at higher precision. Such method allows banks to use own estimates of parameters entering the regulatory formula for minimum capital requirements. On the one hand, IRB's greater complexity makes its administration more expensive. On the other hand, IRB usually produces lower regulatory capital than the Standardized Approach due to its higher risk sensitivity. Basel III presents two IRB approaches – foundation and advanced. The more detailed insight on these methods will be provided in *chapter 5* and *chapter 6* respectively.

4.1 Data collection and analysis

As the aim of the thesis is to illustrate a calculation of capital requirements to credit risk under the regulatory framework, I picked a sample of 69 corporate firms[5] of which 41 are non-defaulted firms and 28 defaulted ones. The non-defaulted corporates were randomly selected from The Forbes Global 2000 – an annual list of the world's 2000 largest publicly listed corporations. The selection of defaulted firms was based on the Moody's Annual Default Studies: Corporate Default and Recovery Rates. My focus was to simulate a sector diversified portfolio, therefore, I chose corporations from 9 industrial sectors as it is illustrated in *Figure 4-1*. The sector division is in accordance with Global Industry Classification Standard (GICS). GICS was jointly developed by MSCI Barra and Standard & Poor's to present complete, consistent set of global sector

[5] Financial firms were not taken into consideration.

and industry definitions. The most up-to-date methodology classifies 10 sectors, 24 industry groups, 67 industries and 156 sub-industries. *Table 4-1* provides an overview of defaulted and non-defaulted corporations across sectors in in the period 2011 – 2015.

Figure 4-1

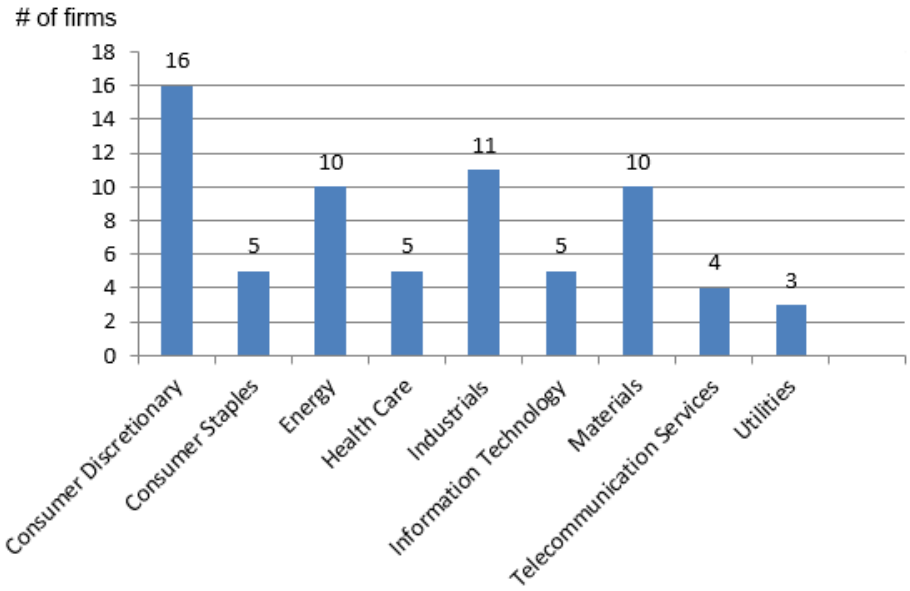


Table 4-1

industry sector	# of defaults	in %	# of non-defaults	in %
Consumer Discretionary	9	32%	7	17%
Consumer Staples	1	4%	4	10%
Energy	7	25%	3	7%
Health Care	1	4%	4	10%
Industrials	3	11%	8	20%
Information Technology	0	0%	5	12%
Materials	5	18%	5	12%
Telecommunication Services	1	4%	3	7%
Utilities	1	4%	2	5%
Total	28	100%	41	100%

Various approaches need slightly different data. The Standardised Approach uses credit ratings provided by external credit rating agencies. I collected long term external issuer ratings provided by Standard & Poor's (S&P) rating agency from the ThomsonONE.com database for the selected portfolio of corporations from 2015. Issuer rating provides a forward-looking opinion about an obligor's overall creditworthiness. Therefore, it is not specific to any particular financial obligation. (Standard & Poor's [b], 2016) Nevertheless, the Basel Accord explicitly recommends

the use of issue rating (specific to a particular obligation) rather than the use of issuer rating for the purposes of risk-weighting claims. The decision to work with issuer ratings in my thesis is essentially prescribed by their availability via electronic sources. In addition, several studies such as Sironi (2000) indicate that issuer and issue ratings are highly correlated albeit external credit rating agencies have a tendency to rate issuer senior debt one or two notches above corresponding subordinated issues rating. (Van Roy, 2005)

Values of defaulted loans were gained from already mentioned Moody's Annual Default Studies and the rest values of loans were simulated in MS Excel via function RANDBETWEEN() and assigned to non-defaulted firms. I consider the loans in the portfolio to be unsecured. It means that they are not covered with any collateral such as fixed asset. For my theoretical portfolio will be created only allowances to cover expected losses. I have decided to adhere the following policy in respect to creation of allowances:

Table 4-2

Allowance policy:

Rating interval	Allowance in %
AAA - A-	0%
BBB+ - BBB-	1%
BB+ - BB-	2,5%
B+ - B-	5%
CCC+ - CCC-	10%
CC+ - C	25%
D	100%
NR	15%

Another information necessary for the calculation of capital requirements to credit risk under the Standardised Approach are days overdue. The days overdue were also simulated under the specified rules. The loans with investment grade ratings, i.e. in the interval [AAA;BBB-], are never overdue. The loans in rating interval [BB+;CC-] and non-rated (NR) loans are overdue at maximum 90 days. Finally, rating category C and D are overdue more than 90 days. I use the threshold of 90 days as it is stated in Basel III as a limit when a default can be considered to happen: *"A default is considered to*

have occurred with regard to a particular obligor when […] The obligor is past due more than 90 days on any material credit obligation to the banking group." (BIS, 2011)

Regarding Internal Ratings Based Approach I will calculate capital requirements to credit risk according to Foundation IRB approach, which allows to model only one input variable – Probability of Default. I will model the Probability of Default with the application of scoring model where the explanatory variables will be presented by companies' financial ratios. Therefore, I needed to collect financial statements for the sample of 69 corporates to create these input variables. Corresponding financial information based on financial statements were obtained from FactSet Fundamentals that is a comprehensive global database providing a company foundation for financial analysis. I collected the data for the period 2011 to 2015 as the modelling approach is based on historical data and created 15 financial ratios and one variable representing size of a firm. Their list together with description is attached in *Annex 1*. For the period 2011 to 2015 is data collected in the following manner: each year in which the firm survives, i.e. firm assigned as non-defaulted (y_{it}=0), is included in the model estimation, while each failure firm, i.e. firm assigned as defaulted (y_{it}=1), contributes to the model estimation only till the year it defaulted. For instance, firm X defaulted in 2013 indicates the data is collected only till 2013 for that firm.

It is desirable to take a deeper look on the data sample. First, I will delete the rows with missing data from the sample so that the final data set consists of 258 observations.

Second, the data set consists of extreme values – outliers – among the observations of created financial ratios constructed from raw data. Such observations could distort the statistical results if they were to be a part of a model. The technique called winsorization is common among literature to avoid extreme values that are consequence of near-zero denominators (Giordani *et al*., 2011). The method is based on replacing the smallest and the largest values with the observations closest to them. In treating the data outliers I will follow e.g. Shumway (2001) and Chava & Jarrow (2004) to set all observations lower than the first percentile of every relevant variable to that value and all values higher than the ninety-ninth percentile of each variable are truncated in the same way.

Finally, it is also important to take into account problems that can appear during a construction of individual financial ratios. The main problem can appear when the nominator and the denominator are both negative. The resulting positive financial ratio has no informative value about the company. In the data set it regards only one financial ratio – return on equity (ROE) – when in some cases are net income as well as shareholders equity both negative. I decided to treat such values so that the useless value of the ratio is replaced by the worst ROE value from every particular industry to which the financial ratio is related.

5 Standardised Approach

BCBS has come with Standardised Approach already in Basel II with the aim to provide more risk sensitive approach to credit risk in comparison with original Basel I. The key difference is in choice of risk weights that represent a fundamental parameter in credit risk measurement. While Basel I only distinguished OECD/non-OECD distinction to assign risk weights to interbank and sovereign claims and to corporates, under Basel II and currently Basel III the risk weights have been linked according to external credit ratings provided by External Credit Assessment Institutions (ECAIs). (Van Roy, 2005)

As it is stated in member states' jurisdictions that allow the use of external ratings in the regulatory standardised approach, only evaluations from credit rating agencies acknowledged as External Credit Assessment Institutions – ECAIs are allowed. Recognition and validation of particular ECAI's assessment, which is based on predefined eligibility criteria, lies on each of the national supervisors. (BCBS, 2015) National supervisors should follow conditions and criteria listed in the Code of Conduct Fundamentals for Credit Rating Agencies[6] (CRA) provided by the board of the international organization of securities commissions (IOSCO). The final choice of the identity and number of ECAIs that banks cooperate with is left to their discretion. The constraints which banks applying the standardised approach to credit risk must follow are that they have to make the choice of ECAIs publicly available and that they have to use ECAIs' ratings consistently. In practice this means that banks are not allowed to "cherry pick" among the credit assessments of various ECAIs with the purpose of shrinking the regulatory capital requirements. (Van Roy, 2005) In order to avoid such situations Basel Committee has come up with a guideline on "multiple assessments" applicable for banks working with more than one external credit assessment institution: (i) When bank selects only one rating by an ECAI for a particular claim, than a risk weight of the exposure is based on this rating; (ii) When bank selects two ratings by ECAIs resulting in different risk weights, than bank uses the higher of these two risk weight; and (iii) When bank selects three or more ECAIs

[6] The final report is available at www.iosco.org/library/pubdocs/pdf/IOSCOPD482.pdf.

with various ratings resulting in different risk weights, first bank should take into consideration two ratings relating to the lowest risk weights. After that, if these two ratings map into the same risk weight, bank should apply that risk weight and if the mapping results in different risk weights, bank should follow the higher one as in point (ii) (BCBS, 2015). It can seem that the guideline for using more ECAIs implies that the banks have no reason to move from one to two or more ECAIs as it can only increase or remain unchanged the risk weight assigned to their exposures. Nevertheless, the reasoning does not take into account the fact that banks may lowered the number of their unrated counterparties by using two or more ECAIs. Since credit ratings can map into lower risk weights in comparison to risk weights for unrated counterparties, banks may thus have an incentive to cooperate with two or more rating agencies rather than with only one. (Van Roy, 2005). In other words, when a bank cooperates with ECAI "A" that does not provide rating to the obligor "X" the bank assigns to that obligor RW of 100 %[7]. But ECAI "B" provides to the same obligor with rating A- that indicates a RW of 50 %. Therefore, it could be convenient for the bank to cooperate with both ECAIs. When using external ratings banks should also determine whether the risk weights assigned to particular exposures are relevant for their inherent risk. In case of insufficient risk weight, bank applies a higher degree of credit risk on that exposure. (BIS, 2011)

5.1 Credit Rating Agencies

Despite the heavy criticism of credit rating agencies for their poor performance during the crises in 1990s and the recent global financial crisis that begun in 2008, in the growing international economic and financial integration, sovereign credit ratings have become one of the most important factors that direct capital flows. Moreover, effects of CRAs on both global economy and sovereign economies have increased. (Haspolat, 2015) Within the financial markets it is not possible for lenders to obtain full information of all borrowers in the world about their financial situation. For securing the continuation and sustainability in financial markets, lenders should be informed about borrowers' ability to fulfil their claims and the existing risks. This fact raises the demand for assessments provided by CRA. To stress the influence of credit rating

[7] Prescribed RW for unrated firms by Basel III is 100%.

agencies on world economy and politics, already in 90s Friedman (1995) points that: *"You could almost say that we live again in a two-superpower world. There is the U.S. and there is Moody's. The U.S. can destroy a country by levelling it with bombs; Moody's can destroy a country by downgrading its bonds."* Nevertheless, due to questionability of credit ratings arising not only from recent global financial crisis CRAs stand in front of the increasing list of critiques. Haspolat (2015) summarized them as follows:

- *"The grading method of CRAs is not sufficiently transparent,*
- *lack of competition in credit rating market,*
- *conflicts of interests because of income model of CRAs,*
- *failure of CRAs to anticipate the crisis and their further deepening of current ones."*

Haspolat (2015) supports in his work the criticism of CRAs that they are not able to foresee the economic crises and that they contribute to deepening of existing crises by making sudden rating cuts.

One of the events from the recent history putting a shadow on CRAs is accusing of the largest credit rating agency – Standard & Poor's – of fraud by the U.S. Justice Department which demanded US$5 billion in restitution (Mattingly, 2013). Nonetheless, also other CRAs are broadly considered as a major contributor to the recent crisis, accused of ratings manipulation, i.e. improving ratings to bad issues. Not only these facts have generated an enormous interest in the industry of external credit ratings among many journalists, researchers and also among average citizens. They focus, for instance, on the impact of CRAs on the world economy and politics or companies – Friedman (1995), Akdemir & Karsli (2012) – on whether the criticism towards them is still valid – Haspolat (2015) – and they are also trying to inquire under which conditions credit rating agencies with insignificant market shares can enhance their positions – Hirth (2014), even they come up with their own models for new credit ratings, new CRAs – Duan & Van Laere (2012), Hirth (2014).

As the use of external ratings is the core of the Standardized Approach, also regulatory organs react on the situation around credit rating agencies. Financial Stability Board – an organ monitoring and making recommendations about the global financial system

– came up with Principles for reducing reliance on CRA ratings in 2010[8]. In line with the principles to reduce mechanistic reliance on external ratings, Basel Committee on Banking Supervision introduced in its first consultative document from 2014 a proposal to remove the use of external credit ratings in case of exposures to banks and corporates and assigned the risk weights based on two risk drivers. However, member states expressed significant concerns to this approach and suggested that the complete elimination of the use of external ratings would be unnecessary and undesirable. Some of the arguments put on the table were that the approach would be excessively complex and that it would be highly insensitive to risk. Conceding the restrictions of removing the overall use of external credit ratings, the BCBS suggests in its second consultative document related to the Standardised Approach reintroducing of CRA ratings, in a non-mechanistic manner, for exposures to corporates and banks as well. Nevertheless, for jurisdictions are also suggested alternative approaches that do not allow the use of CRA ratings for regulatory intentions. On the one hand, these suggestions focus on balancing risk sensitivity and complexity. On the other hand, there could be insufficient comparability between jurisdictions using external ratings for regulatory intentions and jurisdictions not using ratings for such intentions. Therefore, this is the aim of BCBS to reduce the variations in outcome between such approaches. (BCBS, 2015)

Regarding corporate exposures, committee proposes so far the following approaches to exposures' risk weighting and credit risk mitigation purposes (BCBS, 2015):

- *"In jurisdictions that allow the use of ratings for regulatory purposes, ratings would be the primary basis to determine risk weights for rated exposures. As in the case of exposures to banks, due diligence could result in a higher risk weight than that determined by ratings. Unrated exposures would be risk weighted at 100%, as under the current approach. The criteria for eligibility of guarantors and financial collateral would be primarily based on external ratings, as in the current approach."*
- *"In jurisdictions that do not allow the use of ratings for regulatory purposes, a lower risk weight of 75% would apply to certain corporates deemed to be "investment grade". Other exposures would receive a 100% risk weight.*

[8] Available at http://www.fsb.org/wp-content/uploads/r_101027.pdf?page_moved=1.

"Investment grade" entities and debt securities issued by them, would be allowed as eligible credit risk mitigants."

- *"In all jurisdictions, exposures to small and medium entities (SMEs) in the corporate exposure class would receive an 85% risk weight."*

5.2 Calculation of capital requirements under Standardised Approach

The Standardised Approach has always linked higher risk weights to riskier assets. The methodological approach as well as the risk weights themselves was materially improved within Basel II in comparison to Basel I, and it has been hereafter refined within the scope of Basel III. As the financial crisis proved, what does not need to be so risky in calm period may abruptly turn out to be very risky during a systemic crisis. Something that seems totally risk-free may appear to have rather big tail risk. (Hannoun, 2010) The new regulatory framework aims, for instance, at expanding the list of exposure classes, altering particular amounts respective to those exposure classes and making changes in the list and classification of off-balance sheet items to upgrade not only the Standardised Approach to reflect developments on financial markets and inflation (CRD IV, 2013).

The list of exposure classes under the scope of Basel III consists of, for instance, exposures to sovereigns, exposures to non-central government public sector entities, exposures to multilateral development banks, exposures to corporates, retail exposures, equity exposures etc. To each of the classes is either applied a range of risk weights categorized according to particular external rating groups or there are stated assumptions and requirements that indicate specific risk weight as it is e.g. in the case of exposures to sovereigns.

This work is based on the portfolio of corporate firms, therefore, I will be interested only in the exposures towards them. As it was already mentioned above, regulatory approach assigns risk weights to particular exposures according to bucket scheme. Basel accord presents the mapping process using external ratings from Standard & Poor's (S&P) rating agency, nevertheless, it does not make any commitment for the user of standardised approach to apply S&P external ratings. The following *Table 5-1*

simulates the mapping process of risk weights to credit ratings buckets for corporate exposures for three biggest external credit rating agencies – S&P, Moody's and Fitch.

Table 5-1

Assessments			Risk weights
S&P	**Moody's**	**Fitch**	**Corporates**
AAA to AA-	Aaa to Aa3	AAA to AA-	20%
A+ to A-	A1 to A3	A+ to A-	50%
BBB+ to BBB-	Baa1 to Baa3	BBB+ to BBB-	100%
BB+ to BB-	Ba1 to Ba3	BB+ to BB-	100%
B+ to B-	B1 to B3	B+ to B-	150%
CCC+ and below	Caa1 and below	CCC+ and below	150%
Unrated	Unrated	Unrated	100%

Source: Based on BIS (2011), corporate exposures

Calculation of minimum capital requirements for credit risk under Basel III is prescribed by the following equations:

$$RWA_i = A_i \times RW_i \tag{1}$$

$$CR = \sum_{i=1}^{n} RWA_i \times 8\% \tag{2}$$

where: A_i = Asset i (i=1,…n)

RW_i = risk weight attached to asset i

RWA_i = risk-weighted asset i

CR = capital requirement.

As presented in equation (2), the minimum amount of regulatory capital for credit risk that bank must hold remains at 8% level of its risk-weighted assets.

Calculation of capital requirements for credit risk under the Standardized Approach is in this work performed on the portfolio of corporate loans which present the exposures (assets) that have to be risk-weighted. However, before the multiplication of the exposure with the relevant risk weight, as shown in equation (1), which has been mapped consistently with the *Table 5-1*, I have to according to Basel III deduct specific credit risk adjustments and then weight the exposure. By credit risk adjustments are

meant allowances in this thesis, whose calculation follows allowance policy specified in *Table 4-2*. In the mapping process is also necessary to take into account another Basel rule which treats the risk weights for defaulted categories in the following manner: (i) when the created allowance is greater than 20%, the assigned risk weight corresponds to 100%, (ii) when the created allowance is less than 20%, the assigned risk weight corresponds to 150%. Mentioned defaulted category is characteristic for loans more than 90 days overdue. After that, I follow equation (1) to obtain risk-weighted assets which are then multiplied by the 8% level characteristic for minimum capital requirements as stated in equation (2). The portfolio together with parameters influencing the quantification of capital requirement under the Standardized Approach such as allowances and days overdue is enclosed in *Annex 2* of the thesis. The minimum capital requirement arising from simulated corporate portfolio for one-year horizon amounts to:

$$\boxed{CR = 354\, mill\ EUR} \tag{3}$$

The result will be discussed in *chapter 7*.

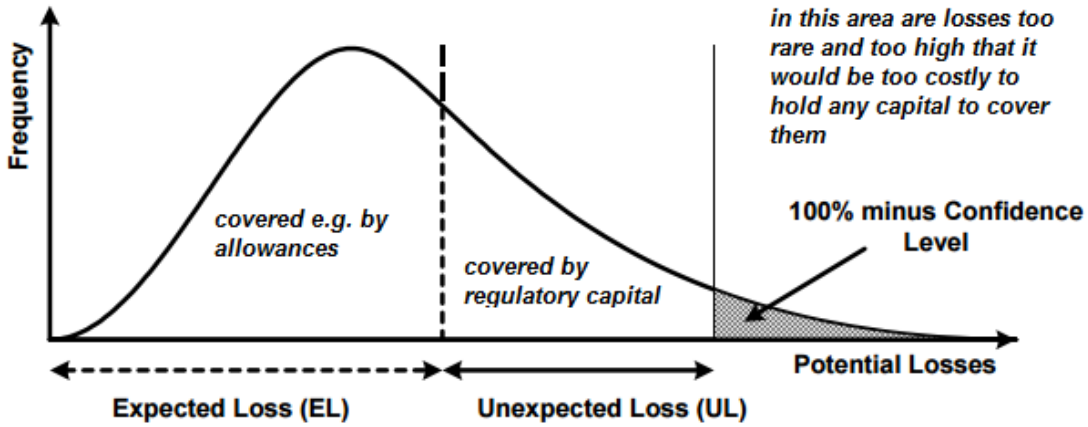
6 Internal Ratings Based Approach

Another approach to calculation of minimum capital requirements to credit risk called the Internal Ratings Based approach has its roots also already in Basel II. Under the enhanced regulatory framework – Basel III – the IRB approach is not materially altered. An effort to create better framework for regulating bank capital is based on internal evaluation of risk parameters subject to particular minimum requirements and agreements by the relevant national supervisory authority. Banks that are permitted to apply IRB approach, so called IRB Banks, are subject to strict range of minimum standards to be able to prove the comprehensiveness and integrity of their capabilities to internal credit risk assessment. (Allen & Overy, 2014, BIS III, 2011)

The IRB approach builds on the notions of expected and unexpected losses. The anticipated average amount of losses that a bank will suffer over a measurement period refer to expected losses. On the contrary, the unexpected losses (UL) belongs to other losses which means that they exceed the average level of anticipated credit losses and in comparison with EL they occur less frequently and consists of larger amounts. (Allen & Overy, 2014)

The bank must protect itself against insolvency by covering both EL and UL with sufficient financial resources such as capital, write-offs and allowances. Following figure illustrates the difference between these two losses.

Figure 6-1



Source: BCBC (2005)

The calculation of EL is based on three risk parameters – probability of default (PD), loss given default (LGD) and exposure at default (EAD). We should take into account that EL do not constitute risks from a credit portfolio but rather, it should be perceived as the costs of doing business that are covered by already mentioned write-offs and allowances, for instance. On the other hand, the regulatory capital requirements are used to cover UL. For a single exposure, the level of expected loss is evaluated by the formula (4). The amount of EL for the whole portfolio is only the sum of ELs of individual exposures.

$$EL = PD * LGD * EAD \tag{4}$$

The parameters used for calculation of UL and thus, for calculation of capital requirements, are equal as in the case of EL. Depending on which credit risk assessment approach a bank using IRB adopts, it can employ its own internal models to evaluate these variables. (Allen & Overy, 2014)

Basel Accord provides banks with two IRB credit risk assessments methodologies – the Foundation Internal Ratings Based Approach (FIRB) and Advanced Internal Ratings Based Approach (AIRB). Both approaches allow banks to apply own internal models for estimation of PD. Probability of default is the only risk parameter that can be evaluated internally by banks using the FIRB approach. Other components are preset within the regulatory framework for them. Conversely, the banks using AIRB approach are allowed to estimate all the variables – PD, LGD and EAD – by applying internally developed models and have to use the calculated effective maturity M of exposures. All the estimations and calculations are subject to the regulatory review. (BIS, 2011) Regarding data necessary for modelling of parameters the IRB Banks are obliged to develop and apply a reliable system so that the data – loss statistics – can be gathered, stored and employed over a long period of time (Allen & Overy, 2014).

The role of national regulators is based on supervision of the IRB Banks so that they approve and validate banks' internal rating models to ensure the compliance and appropriateness of such models for regulatory capital calculations. The financial institutions that want to implement IRB method have to follow a designed standard model lifecycle. The lifecycle of every model consists of three phases – assessment,

implementation and validation. The regulators have set specific requirements for each of the phases.[9]

To be able to calculate regulatory capital requirements under the advanced approach, the development of model for LGD is necessary. However, its modelling is beyond the scope of the thesis and therefore, I will take into consideration only foundation approach further on in the simulation of capital requirements quantification.

The formula for calculation of capital requirements (*CR*) used in IRB approach for corporate firms is as follows:

$$CR = 8\% \cdot RWA \tag{5}$$

where the RWA calculation ensue the following formula (CRR, 2013):

$$RWA = K(PD, LGD, M) \cdot 12.5 \cdot EAD \tag{6}$$

The function representing the derivation of capital (*K*) is set by the regulator in the form (BIS, 2011):

$$K = \left(LGD \cdot N\underbrace{\left(\frac{1}{\sqrt{1-R}} \cdot G(PD) + \underbrace{\sqrt{\frac{R}{1-R}} \cdot G(0.999)}_{B} \right)}_{A} - LGD \cdot PD \right) \cdot \frac{1 + (M - 2.5) \cdot b}{1 - 1.5 \cdot b} \cdot 1.06 \tag{7}$$

where: *N(x)* = the cumulative distribution function for a standard normal random variable

G(Z) = denotes the inverse cumulative distribution function for a standard normal random variable

R = denotes the coefficient of correlation, is defined as:

[9] For detailed information about the individual phases please refer e.g. to BIS (2011).

$$R = 0.12 \cdot \frac{1-e^{-50 \cdot PD}}{1-e^{-50}} + 0.24 \cdot \left(1 - \frac{1-e^{-50 \cdot PD}}{1-e^{-50}}\right) \tag{8}$$

b = the maturity adjustment factor, which is defined as:

$$b = \left(0.11852 - 0.05478 \cdot \ln(PD)\right)^2 \tag{9}$$

When we take a deeper look at the formula (7), it refers to a single risk factor model where a single factor here is correlation. Part A is a proxy for systematic exposure to general economy. If we assume that credit asset has no systematic risk (R=0) (no systematic exposure to general economy) than part B cancels out and we are on the level of EL as LGD*PD is substitution for EL. In the case where R>0, higher correlation means greater systematic risk or in other words higher exposure of the asset to general economy. Moreover, regarding the maturity adjustment, regulator includes it in the formula to take into consideration potential credit quality deterioration of exposures that have longer maturity. Basel has come up with the suggestion of average maturity to be 2.5 years applicable in FIRB. The longer the maturity the greater the credit risk and the higher the capital requirements. Such an effect comes to light in case of AIRB. Finally, the formula is introduced such that the regulatory capital should be able to cover UL at the confidence level of 99.9 % over a one year horizon. In other words, there is a chance that in one case out of one thousand the bank will suffer credit losses higher than what could be covered by regulatory capital. We can notice that such an approach reflects Value-at-Risk methodology.

As already mentioned above, I will apply the foundation IRB approach to determine the minimum capital requirements. Hence, I will perform modelling of the only parameter – probability of default – whereas the others (LGD, EAD and M) are preset by regulator. In the regulatory framework is proposed that the value of LGD for senior exposures without eligible collateral should be at the level of 45 % while for subordinated exposures without eligible collateral should be at the level of 75 % (BIS, 2011). I assume that the portfolio in this thesis is composed only of senior exposures, therefore, I will use the recommended level of 45 % for LGD in the computation. Regarding maturity when a bank does not use own estimates of LGD then it should apply to exposures arising from repurchase transactions or securities or commodities

lending or borrowing transactions a maturity of 0.5 years and to all other exposures a maturity of 2.5 years (BIS, 2011). In our case the portfolio falls into the category of other exposures, hence, I will utilize the value of 2.5 years for M. Finally, Exposure at Default in general increases with possible forthcoming default event because the obligor wants to utilize the maximum available amount to prevent financial distress as in the case of e.g. overdrafts. However, for the purposes of this thesis I will take as EAD the accounting value of the corporate loan adjusted for created allowances. This approach allows me to fairly compare SA with IRB.

6.1 Probability of Default

The first step in a process of assessing the credit exposure and potential losses for financial institutions or investors is estimating of default probabilities of individual obligors in a portfolio. Once we know the particular probabilities of defaults, then there is a straightforward way of estimating the associated loss distribution, which serves as a key element for assessing risks and vulnerabilities in the financial and corporate system.

Nevertheless, we can face limitations on data availability when estimating probabilities of default. Fortunately, there exist some models which are out of these limitations. A possible way of classifying these models is following: fundamentals-based (accounting-based) models and market-based models. The first group of models is based on accounting, economic and systematic market factors, and ratings information, while the second group relies on security prices. (Chan-Lau, 2006) To make estimates of defaults market based models apply option-pricing theory. A problem stemming from this type of models is caused by the fact that they cannot be used directly for privately held companies as they are based on market values and the volatility in market value returns. In spite of that I would like to provide some insight into market-based models with an emphasis on typical model of this type – Merton model as it represents another possible approach to credit risk modelling.

However, for the simulation purposes of the thesis I will employ one of the fundamentals-based models. Qualitative dependent variable models such as logit and probit are used for estimation of fundamentals-based models. In this case, I will focus on a use of logit model.

6.1.1 Market-based models

Basic idea of market-based models, also called structural models, is founded on modeling of behavior of the total value of company's assets. Thus, Bielecki *et al.* (2006) refer to it also as the value-of-the-firm approach or Chacko *et al.* (2006) name it asset-value models. This approach indicates company's default if its assets' market value is smaller than the obligations or debt it has to pay. Therefore, it assesses company's creditworthiness with respect to its balance sheet and capital structure. Substantial issue of structural approach lies in the hardly observable value of company's assets. However, its debt as well as the market value of its stock equity is observable. Furthermore, it was proved that we can model default as an option on firm's debt. It follows that we are able to derive market value of company's assets by using option pricing theory. Black & Scholes (1973) and Merton (1973, 1974) pioneered this relationship of assessment of risky debt and option pricing theory and gave birth to the first classical structural model – the Merton model. (Chacko *et al.*, 2006). Merton model is based on several characteristics which Kealhofer (2003) presents as follows:

- *"The company has a single debt liability, has equity, and has no other obligations.*
- *The liability promises a continuous fixed coupon flow and has an infinite maturity.*
- *The company makes no other cash payouts (e.g., equity dividends).*"

In this model we suppose that the market value of the firm's assets proceeds as a lognormal process (Kealhofer, 2003). Basis of the Merton model is a fact that the firm's equity is perceived as a call option on its assets (Merton, 1974). The firm's debt is presumed to be a zero coupon bond with a nominal value B that matures at time T. In the case when the company value V is higher than the nominal value B at the maturity day, bondholders get paid the whole nominal value B and the remaining V_t-B represents the value of equity that appertain to the stockholders. If the firm value V declines under its debt B, it indicates the firm is going to bankrupt and the debt holders obtain the liquidation value while the stockholders do not obtain anything. The described process imply that the debt B constitutes the default barrier that in option terms can be perceived

as the exercise price and the company value V can be perceived as the price of the underlying asset. Based on these assumptions we can apply the call option formula as follows:

$$E = VN(d_1) - Be^{-rT} N(d_2) \tag{10}$$

where:

$$d_1 = \frac{\ln\left(\frac{V}{B}\right) + \left(r + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}} \quad \text{and} \quad d_2 = d_1 - \sigma\sqrt{T} \tag{11}$$

and where: $N(.)$ = cumulative probability distribution function for a standardized normal distribution

r = risk-free interest rate

σ = instantaneous standard deviation (volatility) of underlying's price changes (computed from log price relatives), (Dědek, 2013).

Merton (1974) applied in his study the equations to specify the value of a firm's equity and subsequently applied a parity relationship to infer the value of the risky debt. The theory provides us also with the estimation of the probability of default. As presented by Charitou *et al.* (2008) variable $N(d_2)$ is considered to be the risk-neutral probability of the company's solvency at maturity date, and therefore, $1-N(d_2)$ represents the probability that the company will default. Moreover, the actual default probability can be estimated when the risk-free interest rate in the equations (10) and (11) is replaced by the expected asset return (Gray & Malone, 2008).

As a variation of classical Merton model was developed KMV-Merton model by KMV Corporation. The Corporation did not extend exactly the original Merton model from 1974, however, it deploys a Vasicek version of Merton model from 1984. It is empirically proven that the results from this model better fit to the value of corporate bonds in comparison with the approaches that use agency bond ratings. (Kealhofer, 2003).

Nevertheless, what about the accuracy of this Merton model? Afik *et al*. (2012) concluded that there exist some issues which reduce the model's accuracy. The paper

also provides a few ways how is possible to improve the model accuracy. They investigate the sensitivity of the model's default predictability to its parameter specifications – the default barrier, the expected return on firm assets, firm assets return volatility. The data used for the investigation were picked from the merged CRSP/Compustat database for the period 1988-2008 and also from rating agencies reports (1988-2009) – Standard and Poor's and Moody. A Receiver Operating Characteristic (ROC) curve was constructed for each chosen specification. There are two types of investigating of default model goodness. Afik *et al*. (2012) focus on one of them – Model's Power – in other words, how the firm is able to differentiate a defaulting company from a non-defaulting one. On the basis of their examination they drew a conclusion that on the one hand, the model is of low sensitivity to the default barrier specification, on the other hand, expected return on firm assets specification as well as firm assets return volatility specification are important and under current usage of historical values for both equity returns and equity volatility instead of forward looking values this is the issue leading to decrease of the ability to differentiate defaulting company from non-defaulting one.

Also Bharath & Shumway (2004) tried to examine in their study the accuracy of KMV-Merton model. The investigation was based not only on different dataset but also on different approach in comparison to Afik *et al*. (2012). Nonetheless, they concluded that the model does not provide a sufficient statistic for the default probability.

Attitudes in structural credit modeling have evolved over time. We can notice some changes in stating the assumptions of particular models – *e.g.* relaxing or adding new ones. As an example of evolving and extending models over time we mention for instance, Black and Cox, Geske and Longstaff and Schwartz model (Lyden & Saraniti, 2003).

6.1.2 Accounting-based models

Methods using accounting-based models are a standard part of risk management processes in financial institutions. The models generate a score representing the firm's creditworthiness. Therefore, it influences a decision of financial institutions whether to provide to a possible obligor a loan or not. For the estimation of scoring models we use

clients' historical data and we obtain the estimation of the probability that the obligor will default. (Loeffler & Posch, 2011)

There exist several factors which can influence borrower's probability of default (PD). When we focus only on a portfolio of corporate clients, their PD can be affected, for instance, by level of company's leverage, cash flows or profitability. Credit scoring (accounting based) models use accounting information as was mentioned in *chapter 6.1*. These types of models were implemented long time ago. Already in 1932 Fitzpatrick compared financial ratios of failed firms with those of successful firms and found out that the PD was connected with individual characteristics of corporates. Several decades later Beaver (1966) investigated the predictive ability of financial ratios. He came up with a univariate analysis where he examined a sample of 79 failed firms, consisting of both bankrupt firms and firms facing other financial problems. He detected that Net Income/Total Assets and Cash Flow/Total Debt were two best predictors of failure.

One of the most famous example of a scoring model is Altman's Z-score. Altman (1968) developed the first multivariate model for bankruptcy classification. His model was based on a statistical method called Multiple Discriminant Analysis (MDA) where he combined five empirical variables estimating the firm's bankruptcy as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.99X_5 \qquad (12)$$

where: X_1=Working Capital/Total Assets

X_2=Retained Earning/Total Assets

X_3=EBIT/Total Assets

X_4=Market Value of Equity/Book Value of Liabilities

X_5=Sales/Total Assets.

The higher the explained variable, the lower the probability of default of possible obligor. Altman also set the particular thresholds identifying the level of default probability. If the Z<1.8 there is a high chance of default; if 1.8<Z<2.7 there is a moderate chance of default. If 2.7<Z<3.0 we should be on alert; if the Z>3.0 default is unlikely. He was the first researcher who developed multivariate statistical model discriminating non-failure from failure companies. Altman used multivariate

discriminant analysis where the initial sample contained 66 companies with 33 companies in each of the two categories (failure and non-failure). Altman employed the variable X_1 thanks to its ability to measure liquid assets in relation to the company's size. This measure predicts more effectively than the widely used acid and current ratio. X_2 serves as a measurement of a company's earning power; failure rates are closely linked to this variable. Operating efficiency separated from leverage impacts is measured by variable X_3. From this part of the formula stems that operating earnings are crucial for a long-run viability. By using the X_4 ratio Altman adds a market influence to the equation; the upcoming problems may be signalized by security price changes. The last of the used ratios – X_5 – is considered to be a standard turnover measure. However, this variable differs markedly across industries. One year prior to the failure the model was able to classify 95% of the total sample correctly, which is very high percentage. However, the longer was the prediction time, the bigger was the misclassification of failed companies. This fact was supported by a study performed by Deakin (1972). He confirmed that with an increasing number of years preceding the bankruptcy the predictive ability of Altman's Z-score declines. He pointed out also on the methodological issue of Altman's model. Namely, random selection of observations in both groups, non-failed and failed, belongs to the basic assumptions of MDA. However, Altman (1968) used a pair-matched sample approach. Deakin utilised in his study a sample of randomly selected 23 survival firms and 11 failure firms and developed bankruptcy prediction model. Up to three years before the failure the classification error was on a relatively low level: 3 – 4.5 %. However, for the fourth and the fifth year before the failure the classification error rapidly increased to 21 % and 17 %.

Altman and other previous researches were criticized for applying MDA for predicting failure, for instance, by Ohlson (1980). The reasons stem from the statistical assumptions imposed by using MDA that are hard to comply. Some of the assumptions are, for example, the distribution normality of all independent variables and the same variance-covariance matrices for both groups of firms. Ohlson presented in his work his own prediction model that uses a statistical approach called logistic regression. Unlike MDA this approach is not based on such strict assumptions (Ohlson, 1980). He applied the logistic regression to a sample of randomly chosen 2 058 listed non-failed

firms and 105 listed failed firms. The model consists of together nine financial variables, some of them are similar to ones in Altman's Z-score such as leverage ratio, working capital ratio and return on asset ratio. Moreover, Ohlson included two dummy variables. One dummy variable equals one for firms with negative net income for the last two years and the other dummy variable stays for firms with negative equity. Firms with negative equity have, according to Ohlson, significantly higher probability of going bankrupt. Therefore, it is reasonable to use a variable that take into consideration such effect. From the original nine variables included in the model only the following four were statistically significant: Net Income/Total Assets, Working Capital/Total Assets, Total Liabilities/Total Assets[10] and Size. The classification accuracy of Ohlson's logit model is on the level of 96.3 %.

6.1.2.1 Industry Effects

A lot of researches have conducted similar studies such as Ohlson (1980). Nevertheless, many existing models is constructed in a general way so that the estimation is performed on a sample of firms from different industries without taking into consideration how the industry effects may influence the results. Why such general models can be less accurate compared to models employing industry effects can be supported by examining average financial ratios across various industries. For instance, an average sales to total assets ratio is 1.15 for US mining industry while for US health care industry the ratio is 0.58 (Brandow Company, 2012). Implementation of this ratio in the original Altman's Z-score with a positive sign indicates that a higher coefficient's value leads to a higher score and consequently to a lower risk of default. Therefore, when we apply Z-score model on both mentioned industries, it would result in a lower score for health care industry (all other variables being equal), despite the default risk may not be higher in that industry. It is reasonable to explain at least partly the variation between average ratios by structural differences across industries. Therefore, taking into account industry effects may lead to an enhanced estimation of risk of default.

After the years, Altman presented variations of classical Z-score model in his studies in *e.g.* 2000 and 2006. Altman (2000) adapted his former Z-score to privately held

[10] By Total Liabilities is through the whole thesis meant the debt of a firm without equity => Total Liabilities + Equity = Total Assets

companies known as Z'-score. The difference stems from the substitution of the variable market value of equity/book value of debt with similar one using only book values. Nevertheless, due to the shortage of private company data base the model uses data from publicly held companies which is considered to be a drawback of the model. (Altman, 2000) Another Z-score version comes from the study of Altman & Hotchkiss (2006). They propose the alternative Z''-score model adapted to non-manufacturing firms. The variable X_5 representing sales/total assets is omitted from the altered scoring formula as according to Altman this ratio is likely to be crucially higher for service and retail companies compared to the manufacturing ones. It means, when the original model would be used to estimate the bankruptcy prediction in non-manufacturing companies, the resulting scores would underestimate the bankruptcy prediction for these companies because of their lower capital intensity (Hayes *et al*., 2010).

Adaptation of models also to other industries has been common among literature, for instance, construction industry (Makeeva & Neretina, 2013), trading industry (Aloy Niresh & Pratheepan, 2015) and hotel industry (Diakomihalis, 2012). The US restaurant industry was investigated by Kim & Gu (2006). They employed both MDA and logistic regression for modelling bankruptcy risk. Only two financial ratios serve as the inputs to both models in their study – EBIT/Total Liabilities and Total Liabilities/Total Assets. Kim & Gu (2006) research attracts attention for two reasons. The both employed methods performed equally effective in predicting restaurant bankruptcy. Moreover, regardless of using only two explanatory variables, MDA as well as logistic regression demonstrated a high out-of-sample prediction accuracy with 93% of all firms correctly classified.

However, the models employing industry effects may have some drawbacks. The question how the bankruptcy-indicating explanatory power for various financial ratios differs among industries is not answered by these models. As the financial ratios differs as well as used time periods in the estimation of the models, the comparison of such models with industry effects may not be very dependable.

6.2 Estimation of PD

At the beginning of this chapter I would like to stress the fact, that underlying portfolio used for quantification of credit risk capital requirements in this thesis is not

representative and is quite small, therefore, the estimated PDs may not be as accurate as should be in reality. Nevertheless, for the simulation purposes of this thesis I do not consider it a problem as the main objective is to present possible applications of regulatory approaches and will take it into consideration in final discussion of results.

Since the 1960s when rating and default prediction studies have occurred, statistical models based on financial statements have become ubiquitous in banking sector. With the introduction of Basel Accord known as Basel II as well as the newest version Basel III the advancement of such models has been further stimulated, as it requires banks to use model-driven estimates of the PD as a basis for deriving risk-based capital.

In this thesis I will use a modelling framework – logistic regression – to specify a scoring model. The score summarizes the information contained in inputs – financial ratios – that influence probability of default. The reasons for the selection of logistic regression are its statistical properties and similarities to multiple regression. Another option which has often been applied when predicting the bankruptcy (e.g. Altman, 1968) would have been multiple discriminant analysis. However, as it was already discussed above, MDA approach used in many finance and business researches suffer from statistical and methodological issues (Eisenbeis, 1977). In comparison to MDA, logistic regression is not based on strict statistical assumptions such as normality of all explanatory variables and is considered to be much more robust technique.

The logistic regression comes from a simple linear model (Cardoso *et al*., 2013):

$$S_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_L x_{iL}\,, \tag{13}$$

where S_i denotes the score in a state i, x represents the inputs – financial ratios (their number is L), and β the coefficients (weights) attached to them.

In the model there is an information about default stored in explained variable y_i. It is equal to 1 whether the company defaulted in the year following the one for which we have gathered the input values, and zero otherwise. What we need to do in the scoring model is to link scores to probabilities of default. For the mapping, I will use a cumulative probability distribution function, more specifically, a function with logistic distribution. The function guarantees that the dependent variable is constrained to the

interval (0, 1) which is what we require when the outcome is default probability. The logistic distribution function $\Omega(k)$ is defined as: $\Omega(k) = \exp(k)/(1+\exp(k))$.

$$pd_i = \Omega(k) = \frac{\exp(k)}{1+\exp(k)} = \frac{1}{1+\exp(-k)} \tag{14}$$

When we apply the formula (13) into formula (14) we get (Loeffler, Posch, 2011):

$$pd_i = \Omega(S_i) = \frac{1}{1+\exp(-\beta' x_i)} \tag{15}$$

That the logistic distribution function represented by the formula (9) guarantees the outcome values to be in the interval (0, 1) is supported by the following reasoning. As k approaches minus infinity, $\exp(-k)$ approaches infinity and therefore, pd_i has a lower limit of 0. As k approaches infinity, $\exp(-k)$ approaches 0 and therefore, pd_i has an upper limit of 1.

The models using logistic distribution function where we map the particular information to probabilities are called logit models. In comparison to multivariate linear regression, the logit model is not assessed by applying the method of Ordinary Least Squares (OLS). Instead, for the estimation of the coefficients β is used another estimation method called Maximum Likelihood. Unlike OLS which minimizes the squared error terms, the maximum likelihood method maximizes the probability of observing the given default behaviour (Loeffler & Posch, 2011).

Nevertheless, logistic regression's property – form of the regression coefficients – makes it tricky to interpret. Coefficients in an ordinary multiple regression can be interpreted as the change in the explained variable that is caused by a one unit increase in the explanatory variable. In the logistic regression the interpretation is not as straightforward as the coefficients reflect variations in the log of the odds ratio. However, by exponentiation of the estimates, they can be interpreted as the variation in the odds ratio when the explanatory variable changes (Hair *et al*., 2010).

6.2.1 Financial Ratios

One of the aims of the thesis is to find such a combination of inputs in the model that provides the best explanation of historical default behaviour on the dataset. There exists a large number of various financial ratios. I chose 15 of them plus a variable indicating

size of a firm which may have a potential influence on obligor's probability of default. The selection was based on research literature such as Altman (1968), Ohlson (1980), Low *et al.* (2001), Hassani & Parsadmehr (2012), and Cardoso *et al*. (2013). The initially chosen financial ratios are listed in *Table 6-1* where we can find also expected impact of particular ratios on default probability which can be theoretically expected. The expectation is based on the previous research as well as on common sense. I divided the ratios into 4 groups as it was done by Hassani & Parsadmehr (2012). Solvency ratios also called leverage ratios look at a company's ability to meet its financial obligations in the long term. They are in interest of business owners as they should prove that the company can services its debt or pay the interest on its debt. Liquidity ratios in contrast with solvency ratios determines a firm's ability to pay off its short-term financial obligations. Generally, the lower the value of the ratio, the higher the probability that the firm will not be able to cover its short-term debts. Another class of financial metrics called profitability ratios assesses how well a company is performing in terms of its ability to generate profit. In other words, the profitability ratios measure efficiency with which a company turns its operating activities into profits. When the value of the ratio for this group of financial ratios presented in *Table 6-1* is higher compared to the same ratio from a previous period, it indicates that the company is doing well. Our last group form activity ratios. Activity ratios are used as indicators of how effectively a firm is using its assets. Generally, the faster the firm is able to turn its production into cash or sales, the more effectively the firm operates.

Table 6-1

Financial ratios

Profitability ratios		Expected impact
Net Profit Margin	Net Income/ Sales	-
Return on Equity	Net Income/ Shareholder's Equity	-
Return on Assets	Net Income/ Total Assets	-
Retained Earning Ratio	Retained Earnings/ Total Assets	-

Activity ratios		
Inventory Turnover	Sales/ Inventories	+
Asset Turnover	Sales/ Total Assets	-
Average Collection Period	(Accounts receivable*365)/ Sales	+

Solvency ratios		Expected impact
Debt to Equity Ratio	Total Liabilities/ Total Equity	+
Debt Ratio	Total Liabilities/ Total Assets	+
Solvency Ratio	(Net Income + Depreciation)/ (Short & Long-term Liabilities)	-
Interest Coverage Ratio	EBIT/ Interest Expense	-
Liquidity ratios		
Current Ratio	Current Assets/ Current Liabilities	-
Quick Ratio	(Current Assets- Inventories)/ Current Liabilities	-
Cash Ratio	(Cash+Cash Equivalents)/ Total Current Liabilities	-
Working Capital Ratio	Working Capital/ Total Assets	-

6.2.2 Univariate Analysis

Existence of many possible combination of financial ratios in the model is more than obvious. Therefore, I will apply several procedures that can serve for the selection of appropriate variables for the final model. First step will be the performance of univariate analysis similarly as was done e.g. by Deakin (1972), Ohlson (1980), Beaver *et al*. (2004) and Keener (2013). *Table 6-2* presents some descriptive statistics of defaulted and non-defaulted companies. The aim of the *Table 6-2* is comparison of accounting variables and taking look at the mean differences of both defaulted and non-defaulted groups of firms. To decide whether group means are significantly different I conducted a t-test with a null hypothesis that there is no difference between the means for defaulted and non-defaulted firms. The null hypothesis of equality was rejected for 9 financial ratios at the significance level of 5 %. That indicates a statistically significant difference between defaulted and non-defaulted firms in these cases.

The financial ratios where we could not reject the null hypothesis of equality are *x1* (TL/TA), *x5* (Sales/Inventories), *x6* (Sales/TA), *x7* (Acc.Receivables*365/Sales), *x12* (Cur.A/Cur.L), *x13* ((Cur.A-Inventories)/Cur.L) and *x14* (Cash & Cash.eqv./Cur.L.).

Therefore, as a part of variable selection process I will omit these ratios from further analysis.

The significant differences between defaulted and non-defaulted firms are in line with our expectations presented in the *Table 6-1*. We expect the positive impact on the probability of default in case of the variable *x2* (TL/TA) which means that the bigger the ratio, the higher might be the probability of default. On the other hand, we expect the negative impact on the probability of default in case of the variables *x3* ((NI+Dep)/TL, *x4* (EBIT/Interest exp.), *x8* (NI/Sales), *x9* (NI/Equity), *x10* (NI/TA), *x11* (RE/TA), *x15* (WC/TA) and *x16* (SIZE) which means the bigger the ratio, the lower might be the probability of default. Therefore, for *x2* is the mean of defaulted firm significantly higher and for the group of variables with negative impact on PD are the means of defaulted firms significantly lower.

Table 6-2

Univariate Analysis						
	Non-defaulted Firms		***Defaulted Firms***		***Equality of means test***	
Variable	***Mean***	***Std. Dev.***	***Mean***	***Std. Dev.***	***t-statistic***	***p-value***
x1	0.9290217	7.961431	3.9065357	18.54394	-0.84026	0.4078
x2	0.6562043	0.2687436	1.1501429	0.4385176	-5.8285	2.391e-06 *
x3	0.1449522	0.232061	0.0045000	0.2150558	3.2342	0.002657 *
x4	30.1785696	73.57072	-0.1258929	1.120315	6.241	2.073e-09 *
x5	31.21950	55.94556	23.32932	32.5841	1.0992	0.277
x6	0.7938478	0.4645817	0.7946786	0.4662555	-0.0089052	0.9929
x7	52.73528	30.32365	58.54946	46.87771	-0.64019	0.5269
x8	0.02529565	0.2031141	-0.24864286	0.3940704	3.6203	0.001119 *
x9	-0.7021652	3.897682	-5.5738929	9.03022	2.8229	0.008626 *
x10	0.01523913	0.141222	-0.09382143	0.1768481	3.1435	0.003638 *
x11	0.3047391	0.2584288	-0.5142500	0.566296	7.5575	2.857e-08 *
x12	1.520696	0.6298636	1.365429	1.064706	0.75573	0.4558
x13	1.138309	0.6351412	0.594750	1.65129	1.7263	0.09531
x14	0.5331348	0.4201315	0.4361071	0.5347786	0.92591	0.3616
x15	0.1066348	0.1861491	-0.3840000	0.4961552	5.1884	1.669e-05 *
x16	9.726352	1.346626	7.224536	1.315078	9.4797	4.161e-11 *

** significance at least at the level of 5 %*

Source: Author's calculations performed in RStudio

6.2.3 Correlations

Before the building the final model we should take into account a possible issue of multicollinearity of independent variables. Since in some cases of the calculation of financial ratios are used the same variables (equity, assets, liabilities, etc.) there exists a real possibility that a multicollinearity problem will occur in the estimated model. Particularly for small and moderate sample sizes such an issue in the estimated model may be a source of inefficiently estimated parameters and high errors, which is further a consequence of the model with high explanatory power and many insignificant variables (Midi *et al*., 2010). To be able to control this problem I decided to follow the methods used by Pervan *et al*. (2011). First, I apply to the variables pair-wise correlation technique. *Table 6-3* presents a correlation matrix where the coefficients with absolute value higher than 0.80 are highlighted as such values indicates a possible multicollinearity problem between the independent variables. From variables showing the high correlation I would discard the one with higher correlations with other variables. Nevertheless, examining the correlation matrix may be helpful in indicating such problem but not sufficient (Midi *et al*., 2010). Therefore, I test the model for multicollinearity also by using Variance Inflation Factors[11] (VIFs) where is performed a linear regression of one discriminating variable as a dependent variable with all other variables as explanatory ones. The VIF is a reciprocal to tolerance of any specific explanatory variable that is defined as follows:

$$Tol = 1 - R^2, \tag{16}$$

where the R^2 is the coefficient of determination for the regression of that independent variable on all remaining ones. The Variance Inflation Factor as a reciprocal to the tolerance is therefore:

$$VIF = \frac{1}{Tol} = \frac{1}{1 - R^2}. \tag{17}$$

When the auxiliary regression results with VIF higher than 5, it implies a multicollinearity problem in the estimated model (Pervan *et al.*, 2011). *Table 6-4* shows the result of performed auxiliary regressions. After the first estimation of VIFs we can

[11] The detail description of VIF is described e.g. by Midi *et al*. (2010).

see that there is a multicollinearity problem in the estimated model constructed from the ratios resulting from univariate analysis – *x2, x3, x4, x8, x9, x10, x11, x15* and *x16*. I discard the variable with the highest VIF – *x10* – and estimate the VIFs again for the model without this variable. This model comprises also variables with VIFs higher than 5, therefore, I discard the variable with highest VIF – *x3* – and perform the estimation again. We can see that the last estimation of VIFs already presents no values above 5.

Table 6-3

Correlation matrix

	x2	***x3***	***x4***	***x8***	***x9***	***x10***	***x11***	***x15***	***x16***
x2	*1.00*	-0.60	-0.40	-0.35	-0.60	-0.63	-0.46	-0.67	-0.39
x3		*1.00*	0.63	0.60	0.39	**0.85**	0.35	0.34	0.21
x4			*1.00*	0.27	0.12	0.34	0.24	0.21	0.15
x8				*1.00*	0.24	0.61	0.37	0.31	0.27
x9					*1.00*	0.59	0.42	0.59	0.38
x10						*1.00*	0.34	0.42	0.34
x11							*1.00*	0.55	0.32
x15								*1.00*	0.35
x16									*1.00*

Source: Author's calculations performed in RStudio

Table 6-4

Estimations of Variance Inflation Factor

	x2	***x3***	***x4***	***x8***	***x9***	***x10***	***x11***	***x15***	***x16***
1. VIFs	5.998	8.844	1.577	4.396	2.485	**13.582**	5.320	1.445	2.646
2. VIFs	2.983	**7.127**	1.627	5.090	2.105		3.087	1.636	1.908
3. VIFs	2.016		1.122	1.280	1.886		1.409	2.245	1.274

Source: Author's calculations performed in RStudio

Based on the tests for multicollinearity I will omit the financial ratios *x3* ((NI+Dep.)/TL) and *x10* (NI/TA) from the further modelling. *Table 6-5* summarizes the rest of the financial ratios that will be taken into account further in the thesis.

Table 6-5

Description of financial ratios

x2	Total Liabilities/Total Assets
x4	EBIT/Interest expens
x8	Net Income/Sales
x9	Net Income/Equity
x11	Retained Earnings/Total Assets
x15	Working Capital/Total Assets
x16	Size (ln(TA))

6.2.4 Final modelling

In the final step I will apply to the remaining variables a forward stepwise procedure that is commonly used among default prediction literature (*e.g*. Pervan *et al.* 2011, Low *et al*. 2001). The procedure was done in 7 steps where in the final step the logit models' Chi-square is 62.81 with a significance level less than 0.001. The model Chi-square is defined as a difference between the log-likelihood of the full model – model with independent variables and intercept – and log-likelihood of the restricted model – model based only on intercept. The log-likelihood test investigates the null hypothesis that is stated such that the coefficients of all independent variables are zero. In our case given the significance level less than 0.001 we can reject the null hypothesis.

After the stepwise procedure we are left with 6 parameters that will be used in final model estimation. The parameters are – *x2* (TL/TA), *x8* (NI/Sales), *x9* (NI/Equity), *x11* (RE/Total Assets), *x15* (WC/Total Assets) and *x16* (size). The *Table 6-6* reports the results of logistic regression based on these independent variables.

Table 6-6

```
Deviance Residuals:
     Min        1Q    Median        3Q       Max
-2.96402  -0.11253  -0.06231  -0.02738   2.11675

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  4.62600    2.29458   2.016 0.043794 *
x2           2.13964    1.42437   1.502 0.133055
x8          -2.31750    1.07723  -2.151 0.031449 *
x9           0.19279    0.07514   2.566 0.010294 *
x11         -5.11952    1.30192  -3.932 8.41e-05 ***
x15         -2.49074    1.42570  -1.747 0.080634 .
x16         -1.00256    0.29308  -3.421 0.000625 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 177.207  on 257  degrees of freedom
Residual deviance:  51.588  on 251  degrees of freedom
AIC: 65.588

Number of Fisher Scoring iterations: 8
```

Source: regression performed in RStudio

The *Table 6-6* shows that all of the parameters in the model are significant predictors of firm default at the significance level of at least 0.05 except for *x2* and *x15*. Although the variable *x2* is insignificant and *x15* is significant at the level of only 0.1, I will include them in the model as TL/TA and WC/TA are considered to be an important determinant in default prediction. Such argument can be empirically supported *e.g.* by Altman (1968), Ohlson (1980), Shumway (2001), Chava & Jarrow (2004), Pervan *et al*. (2011) and Cardoso *et al.* as their models includes the leverage ratio, respectively WC/TA (Altman, 1968, Ohlson, 1980) to predict bankruptcy.

The signs of the estimated coefficients are in line with simple economic intuition except for ROE ratio *x9*. The model implies the positive relationship between ROE and PD. In other words, the higher the ROE the higher the default probability. Nevertheless, such an effect can be explained in a following manner. A company may attain higher

level of ROE with low levels of shareholders' equity (as it performs as denominator). But the undercapitalized company may compensate the equity-debt site by higher leverage and therefore, it may be more prone to default.

The model implies that highly levered companies are more likely to default, as shown by positive coefficient on total liabilities to total assets ratio (*x2*). On the contrary, the company's probability of default decreases if net income to sales (*x8*), retained earnings to total assets (*x11*) and working capital to total assets (*x15*) increases. Net income to sales as one of the profitability ratios reflects the ability of the company to transfer each gained euro into profits. On the other hand, another profitability ratio – RE/TA – provides an idea of company's ability to accumulate earnings with use of its assets. It serves as a measure of company's earning power. Further, the insight into the firm's liquidity is assured by WC/TA ratio. Its negative coefficient shows that the higher ratio of liquid assets in relation to the firm's size implies the lower probability of default. In the end, the model also controls for the firm size effect by incorporating the natural logarithm of total assets (=*x16*). The negative coefficient of size parameter implies that as firm size grows the PD declines. This reflects the fact that the small entities are more inclinable to default than bigger entities.

Based on the estimated model I cannot confirm the hypothesis that the solvency ratios are superior to the other financial ratios in bankruptcy prediction. The measures of leverage providing us with the insight into the firm's ability to meet its financial obligations in the long term do not seem to be the most significant default predictors for my portfolio. Our model is rather based on the ratios from different groups, specifically combination of profitability, solvency and liquidity ratios and ratio measuring the size of the firm with a certain dominance of profitability ratios. The finding about crucial role of profitability ratios coincides with Makeeva & Neretina (2013). When making conclusions about such hypothesis we should take into consideration the fact that the selection of suitable predictors may be correlated to underlying portfolio. For instance, when modelling default prediction for industry specific portfolio such as e.g. retail portfolio, the use of predictors from different groups of financial ratios may vary. However, based on our model I can say that for bankruptcy prediction is more suitable the use of parameters from various ratio groups. Such an arguing can be supported by empirical models from *e.g.* Altman (1968),

Ohlson (1980), Low *et al.* (2001), Pervan et al. (2011), Makeeva & Neretina (2013) and Cardoso *et al*. (2013).

6.3 Model evaluation

The final step in the modelling of probability of default will be the validation of the model. I will test the discriminatory power – how good the model can distinguish between defaulted and non-defaulted firms – applying two methods: classification matrix and Receiver Operating Characteristic.

6.3.1 Classification matrix for model accuracy

Among studies focused on accounting based prediction models, the usual way of estimated model evaluation is testing its prediction accuracy. By choosing a cut-off value differentiating between both groups of defaulted and non-defaulted firms the model is evaluated based on its ability to classify the firms into these groups. Firms' classification into defaulted and non-defaulted groups is in our case based on a most commonly used cut-off value of 0.5 (Hosmer *et al*., 2013).The technique so called the classification matrix provides us with the accuracy of estimated model. When the non-defaulted firm is correctly classified as non-defaulted it is called specificity (equation (17)). When the firm is classified as defaulted and actually defaulted it is called sensitivity (equation (18)). But on the other hand, it also reflects built-in uncertainties of this estimated model. These uncertainties that are embedded in the model are presented as Type I error and Type II error. Type I error occurs when defaulted firm is classified as non-defaulted one and Type II error occurs when non-defaulted firm is classified as defaulted one.

Table 6-7

Classification matrix

	Observed	
Classified	Non-default	Default
Non-default	*correctly predicted [A]*	***Type I error*** *[C]*
Default	***Type II error*** *[D]*	*correctly predicted [B]*

Source: Hosmer et al. (2013)

$$Specificity = \frac{A}{A+D} \tag{18}$$

$$Sensitivity = \frac{B}{B+C} \tag{19}$$

Both types of errors can be rather costly for a bank. Regarding Type II error the costs are not so obvious as they stem from the bank's foregone business. In other words, it is the amount that the bank could have gained if it had correctly decided to give a credit. On the other hand, the cost caused by Type I error are known for the bank. When the bank provides a credit to a client that subsequently defaults, it will partly lose the profit from interest as well as principle and may suffer costs from collection process and bankruptcy proceedings, for instance.

As already mentioned above, in this thesis a company is classified as defaulted (non-defaulted) company if it has a predicted probability of default greater (less) than specified cut-off value 0.5. The *Table 6-8* shows the results of classification matrix applied on the estimated model. The matrix implies the following outcomes: the sensitivity and the specificity of the model reach 87.5 % and 97 %, respectively; type I error is 12.5 % and type II error is 2.99 %. The overall accuracy of the model attain 96.12 %. But we have to take into account that the classification matrix allows us to evaluate the ability of the model to distinguish only with regard to the chosen cut-off value.

Table 6-8

Classification matrix

	Observed	
Classified	Non-default	Default
Non-default	*227*	*3*
Default	*7*	*21*

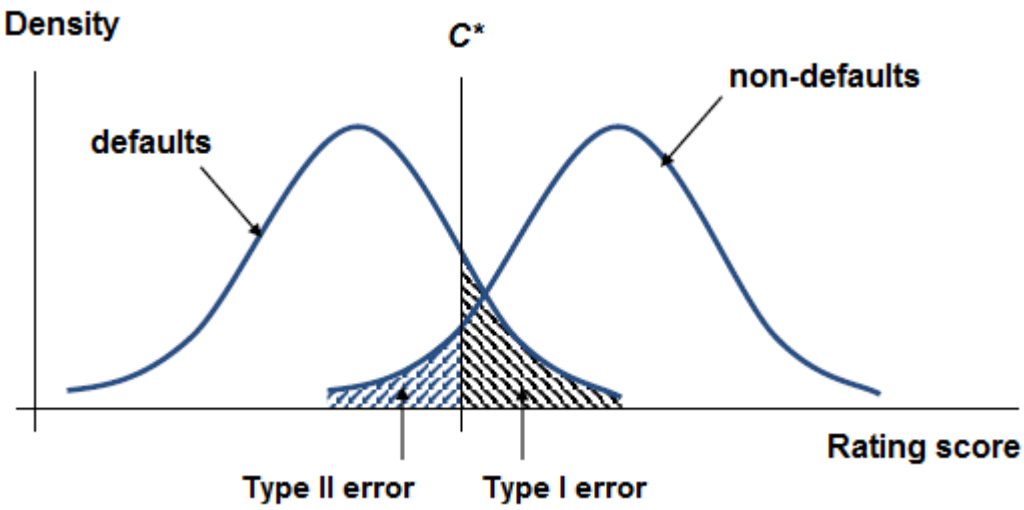
Source: Author's calculations performed in RStudio

6.3.2 ROC and Area under Curve

The final step in the analysis is to investigate how well the estimated model can distinguish defaulted and non-defaulted firms with the use of ROC curve (Receiver Operating Characteristic). Its construction is based on possible rating scores' distributions for defaulted and non-defaulted firms. As illustrated in *Figure 6-2* in the real world these two distribution will overlap. For a perfect discrimination the distributions of both groups would be separate, but such situation is in general not

possible. A cut-off point *C** in *Figure 6-2* represents an optimal value that minimizes costs from both types of errors – Type I and Type II – that occur if we classify defaulter and non-defaulter according to specified *C* value. (Engelmann *et al*., 2003)

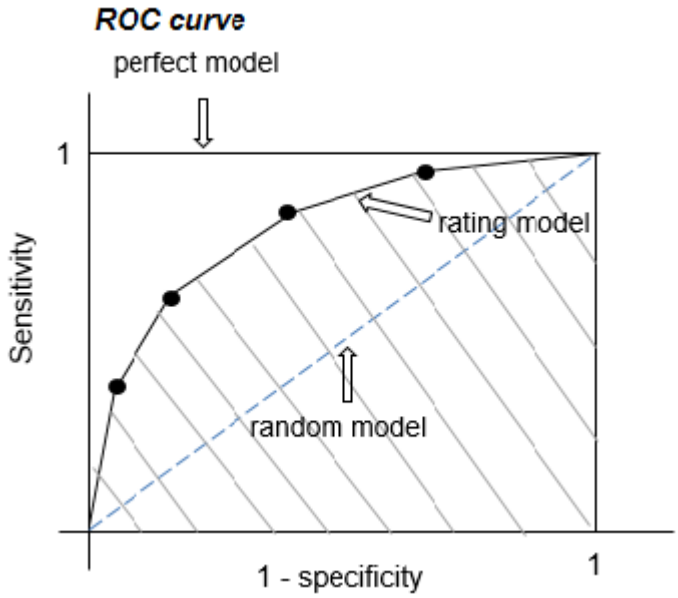
Figure 6-2



Source: Based on Engelmann et al. (2003)

ROC curve provides a more complete description of classification accuracy. As a visualization of model's discriminatory power the curve plots the probability of correctly classified defaults (sensitivity) against incorrectly classified non-defaults (1-specificity) for entire range of possible cut-off values in contrast to the classification matrix. (Hosmer *et al.*, 2013)

Figure 6-3



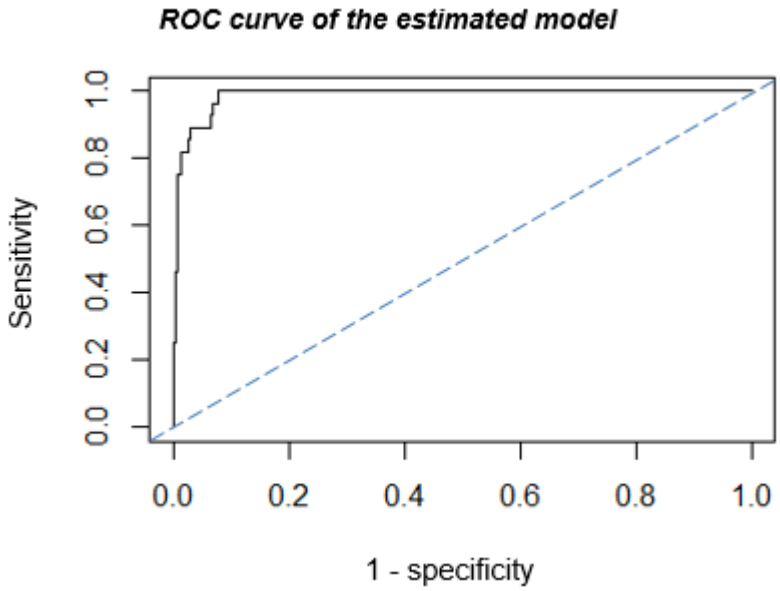
Source: Based on Engelmann et al. (2003)

The performance of the model is better the steeper slope occurs on the left end and the nearer the position of the curve is to point (0, 1). It implies that the bigger the Area under the ROC (AUROC) curve, the better the model. AUROC equalling to 0.5 indicates a random model with no discriminative power. When we have a perfect model then AUROC has value of 1. Both cases are illustrated in *Figure 6-3*. Therefore, in practice the models with AUROC between 0.5 and 1 are reasonable. (Hosmer *et al.*, 2013)

The receiver operating characteristic for our estimated model is illustrated by *Figure 6-4* and simultaneously the area under the curve equals 0.9298[12] which implies the model with very good discriminatory power.

[12] Calculation performed in RStudio with the use of ROCR package.

Figure 6-4



Source: created in RStudio

6.4 Internal rating system creation

When a bank gets an estimated PDs for a particular sample, next step is to determine own rating scale that will set necessary default probabilities for quantification of credit risk capital requirements for actual portfolio. In our case, I employed a logistic regression to estimate the scores, respectively PDs of individual obligors in my portfolio of 69 corporates with data ranging from years 2011 – 2015.

To determine internal rating system it is necessary to set total number of the rating classes forming the rating system as well as thresholds separating these classes. The regulation does not specify the number of rating classes that a bank must have. It only sets the minimum number of groups: *"[…] a bank must have a minimum of seven borrower grades for non-defaulted borrowers and one for those that have defaulted.*" (BIS, 2011)

Since I would like to present two rating systems in this chapter – one derived from regression model from *chapter 6.2.4* and the other based on S&P's transition matrix and S&P's external ratings that will be presenter later in this chapter – I decided to form the internal rating system with 16+1 groups in case of regression model as such system will have a comparable number of groups with the one based on S&P's

mapping. In the next paragraphs I will deal with the first rating system based on regression until stated otherwise.

Regarding the thresholds that distinguish selected rating classes, Basel III only requires: "*A bank must have a meaningful distribution of exposures across grades with no excessive concentrations, on both its borrower-rating and its facility-rating scales.*" (BIS, 2011) Therefore, there can exist many methods how to set the thresholds. In this thesis I will follow Jankowitsch *et al*. (2003) and determine the individual rating groups such that each group consists of the same number of obligors. Therefore, if my underlying portfolio contains 258 observations and the rating system has together 17 classes, each group will be formed from approximately 6 % of all obligors. We can notice that creation of internal rating system is based on the portfolio with historical data (2011 – 2015) and therefore, the creation process apply all available information. Based on stated conditions the scores implied by the logit model determine the threshold values as it is presented in *Table 6-9*. The default probability for each of the rating categories is calculated as an average of estimated PDs within the particular rating category.

Table 6-9

Internal rating system - logit

	Score	logit PD
Rating category I	-9.69 - -8.76	0.01 %
Rating category II	-8.67 - -8.04	0.02 %
Rating category III	-7.99 - -7.52	0.04 %
Rating category IV	-7.51 - -6.96	0.07 %
Rating category V	-6.92 - -6.69	0.11 %
Rating category VI	-6.68 - -6.36	0.15 %
Rating category VII	-6.35 - -6.16	0.19 %
Rating category VIII	-6.14 - -5.96	0.23 %
Rating category IX	-5.93 - -5.49	0.35 %
Rating category X	-5.46 - -5.25	0.47 %
Rating category XI	-5.24 - -4.97	0.59 %
Rating category XII	-4.87 - -4.31	1.03 %
Rating category XIII	-4.15 - -3.60	2.02 %
Rating category XIV	-3.49 - -2.13	5.81 %
Rating category XV	-2.12 - -0.45	19.45 %
Rating category XVI	-0.34 - 1.48	58.51 %
Rating category XVII	1.61 - 11.23	97.59 %

Source: based on author's calculations

We can see that default probabilities increase moving from the best rating category to the worst rating category. It implies that the created rating system is reasonable. Nevertheless, the internal rating system should also comply with historical ratings. That can be check by employing so called cohort method where the particular PDs are determined according to equation (20).

$$PD_j^c = \frac{D_j}{T_j} \tag{20}$$

Where: PD^c_j = probability of default in rating category j

D_j = observed number of defaults in rating category j

T_j = total number of observations in rating category j

j = 1, 2,…, 17

Table 6-10 summarizes calculated cohort probabilities of default and simultaneously compares the probabilities to the ones obtained from logistic regression.

Table 6-10

PDs logit *vs*. cohort method

	logit PD	*Cohort PD*
Rating category I	0.01 %	0.00 %
Rating category II	0.02 %	0.00 %
Rating category III	0.04 %	0.00 %
Rating category IV	0.07 %	0.00 %
Rating category V	0.11 %	0.00 %
Rating category VI	0.15 %	0.00 %
Rating category VII	0.19 %	0.00 %
Rating category VIII	0.23 %	0.00 %
Rating category IX	0.35 %	0.00 %
Rating category X	0.47 %	0.00 %
Rating category XI	0.59 %	0.00 %
Rating category XII	1.03 %	0.00 %
Rating category XIII	2.02 %	0.00 %
Rating category XIV	5.81 %	6.67 %
Rating category XV	19.45 %	20.00 %
Rating category XVI	58.51 %	73.33 %
Rating category XVII	97.59 %	86.67 %

Source: based on author's calculations

The table with cohort PDs implies that our created internal rating system based on regression model is not in accordance with historical default probabilities derived from the sample. Most of the time logit rating system overestimates the historical PDs which will result in higher capital requirements than with a better calibrated rating system. The problem in calibration stems mainly from the insufficient data sample used in this thesis. With this fact in mind, I will use the internal rating system derived from logistic regression to quantify credit risk capital requirements as the objective of this thesis is not to get exact numbers but rather to simulate possible regulatory approaches of bank's risk management to credit risk and discuss the outcomes.

The second internal rating system that will be used for determination of capital requirements is based on transition matrix provided by external credit rating agency. I decided to present this approach as a bank has also possibility to set its internal rating system by accepting external system as their own. To be consistent throughout the thesis I will employ external rating system from Standard & Poor's as such external ratings were used to quantify capital requirements under the Standardised Approach.

As was already mentioned at the beginning of this chapter, this internal rating system consists of together 17 categories. The system is based on the average one-year transition matrix that is derived from the corporate data for the period 1981 – 2015 which is illustrated in *Table 6-11*. Individual PDs from transition matrix are assigned to obligors from actual portfolio according to their external rating that were also used in Standardised Approach presented in *chapter 5*.

Table 6-11

Internal rating system – S&P's

Average One-Year Transition Matrix for corporates (1981-2015) (in %)

From/to	AAA	AA+	[...]	B-	D
AAA	87.08	5.74	[...]	0.00	**0.00**
AA+	2.47	77.29	[...]	0.00	**0.00**
AA	0.44	1.30	[...]	0.02	**0.02**
AA-	0.05	0.12	[...]	0.00	**0.03**
A+	0.00	0.07	[...]	0.00	**0.06**
A	0.04	0.05	[...]	0.00	**0.06**
A-	0.05	0.01	[...]	0.01	**0.07**
BBB+	0.00	0.01	[...]	0.03	**0.12**
BBB	0.01	0.01	[...]	0.04	**0.18**
BBB-	0.01	0.01	[...]	0.17	**0.28**
BB+	0.05	0.00	[...]	0.21	**0.37**
BB	0.00	0.00	[...]	0.37	**0.62**
BB-	0.00	0.00	[...]	0.85	**1.05**
B+	0.00	0.01	[...]	2.56	**2.20**
B	0.00	0.00	[...]	8.42	**4.04**
B-	0.00	0.00	[...]	53.35	**7.21**
CCC/C	0.00	0.00	[...]	8.91	**26.36**

⇨

	S&P's rating	S&P's PD
Rating category I	AAA	0.00 %
Rating category II	AA+	0.00 %
Rating category III	AA	0.02 %
Rating category IV	AA-	0.03 %
Rating category V	A+	0.06 %
Rating category VI	A	0.06 %
Rating category VII	A-	0.07 %
Rating category VIII	BBB+	0.12 %
Rating category IX	BBB	0.18 %
Rating category X	BBB-	0.28 %
Rating category XI	BB+	0.37 %
Rating category XII	BB	0.62 %
Rating category XIII	BB-	1.05 %
Rating category XIV	B+	2.20 %
Rating category XV	B	4.04 %
Rating category XVI	B-	7.21 %
Rating category XVII	CCC/C	26.36 %

Source: Standard & Poor's [a], 2016

Based on the second internal rating system I get another amount of regulatory capital requirements to credit risk. The quantification under the FIRB using these two rating systems is performed in the following *chapter 6.5*.

6.5 Calculation of capital requirements under FIRB approach

As the aim of the thesis is to compare capital requirements to credit risk derived from SA and IRB regulatory approaches, the quantification of such capital under FIRB is based on the same portfolio of corporate loans that was used in *chapter 5.2*. So far, I gained the necessary parameters either by their modelling (PD) or by their determination based on regulatory rules (LGD, M, EAD).

Let us recall the formulas used for quantification of desired capital requirements:

$$RWA = K(PD, LGD, M) \cdot 12.5 \cdot EAD \tag{21}$$

$$CR = 8\% \cdot RWA \tag{22}$$

The function K is preset by regulator where I was allowed according to foundation internal ratings based method to estimate the PD parameter by using internal model

and to determine parameters LGD and M as stated by regulator. The formula *K(PD, LGD, M)* is presented in *chapter 6*.

I estimated the probability of default for every corporate loan in my portfolio using logistic regression and set the internal rating system based on the model that is shown in *chapter 6.4*. As stated by regulator I set the loss given default to the value of 45 % and maturity to the value of 2.5 years. Exposure at default is determined as nominal value of particular exposure adjusted for allowances. With the knowledge of all parameters I can calculate minimum capital requirement to credit risk. Its quantification is performed in MS Excel with a following result:

$$\boxed{CR = 270\, mill\ EUR} \tag{23}$$

All parameter being equal except for default probabilities, I derive the minimum capital requirements using the second internal rating system based on S&P's transition matrix presented in *chapter 6.4*. The quantification is again performed in MS Excel and the result is as follows:

$$\boxed{CR = 172\, mill\ EUR} \tag{24}$$

As well as in the case of Standardized Approach I provide the portfolio with all necessary inputs for the calculation of capital requirements using both internal rating system in *Annex 3* of the thesis.

7 Capital requirements to credit risk – SA *vs*. IRB

In order to prove the hypothesis that the banks reach lower capital requirements using more sophisticated regulatory models I determined minimum capital requirements according to two techniques prescribed by regulator – standardised approach and IRB approach. The quantification methods were already presented in *chapter 5.2* and *chapter 6.5* respectively. Following table shows the outcomes of both techniques.

Table 7-1

	Capital Requirement in mill EUR
Standardized Approach	354
IRB Approach - logit	270
IRB Approach - S&P	172

Source: based on author's calculations

The application of IRB method based on both internal rating systems yields lower minimum regulatory capital requirements to credit risk in comparison to standardised method based on mapping of external ratings. Taking into account the calibration problems with internal rating system I can still preserve the conclusion that IRB method is beneficial in terms of lower capital requirements because the set internal rating system rather overestimates the PDs and therefore, implies higher capital requirements. The difference between SA and IRB amounts to 84 million EUR, respectively 182 million EUR. Therefore the simulated portfolio of corporate firms used in this thesis allows us to prove stated hypothesis.

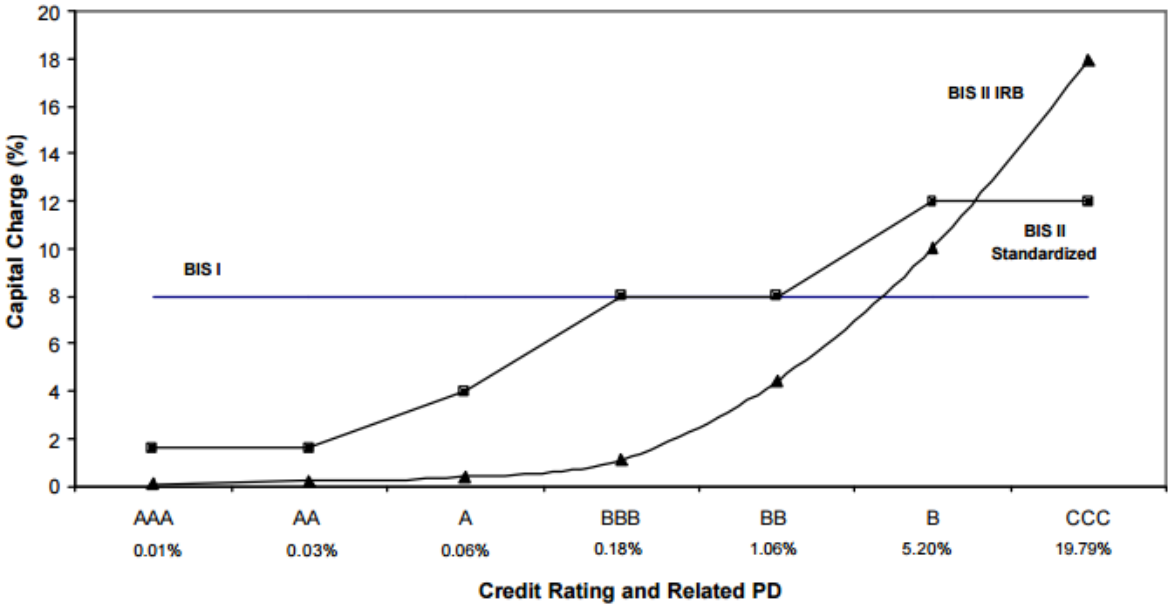
However, what can be quite surprising is that IRB method based on logit rating system yields higher capital requirements than IRB method based on S&P's rating system. I would expect the opposite result as the S&P's rating system reflects external ratings and therefore it should be less risk sensitive than the regression approach. The reason for this situation again may stem from overestimation of historical PDs by derived internal system from logit model that is based on insufficient data sample.

The overall result is in line with the aims of BCBS to allow banks to hold lower level of regulatory capital using more risk sensitive approach. However, according to Stephanou & Mendoza (2005) the capital charge is sensitive to credit rating/PD of

corporate firm and therefore, loans to firms with high rating are expected to benefit from sophisticated regulatory approach, while loans to low rated firms will be penalized. The *Figure 7-1* illustrates the finding of Stephanou & Mendoza (2005). The study investigated Basel I and Basel II methods. However, as the approaches to credit risk capital requirements have not been materially altered in Basel III with respect to Basel II, I consider it as relevant to present their finding.

Figure 7-1

Comparison of capital charge under different regulatory approaches



Source: Stephanou & Mendoza (2005)

Such result is also reflected in this thesis as the created portfolio of corporate loans used for quantification of capital requirements consists mainly loans with ratings between AA to B+. The fact that higher quality portfolio will face lower capital charges and *vice versa* was confirmed also by the earlier study of Jankowitsch *et al*. (2003).

8 Conclusion

Banks next to conducting their own business must also effectively manage many risks stemming from the business to be able to survive in financial industry. With the effort to keep harmonised banking sector a regulator comes to the fore to supervise and influence banks' management and measurement approaches. This thesis focuses on credit risk as one of the main sources of possible adverse impacts on banks' performance and analyse regulatory approaches to credit risk capital requirements that serve as a buffer against losses stemming from that risk.

Basel Committee for Banking Supervision in role of banking regulator issues recommendations in form of Basel Accord that are widely accepted by states around the world and transposed into national discretions. The thesis provide an overview of Basel Accord development and highlights the changes regarding capital definitions as well as capital requirements that come with the most up-to-date version called Basel III. In comparison with previous Basel II, Basel III adds to the 8 % level of minimum capital requirements to credit, market and operational risk also so called capital conservation buffer that should together with 8 % reach 10.5 % RWA at the latest in 2019. Moreover, Basel III introduces another type of capital protection – countercyclical capital buffer – that is a voluntary element of national regulators and should be created to mitigate pro-cyclical dynamics.

The stated hypothesis was that using more sophisticated regulatory models banks reach lower capital requirements. To try to prove empirically this hypothesis I had to first create a portfolio to which I applied two approaches prescribed by regulator – Standardised Approach and IRB approach – that are used to quantify credit risk capital requirements. I chose a portfolio of listed corporates to be able to employ both methods.

After the portfolio selection and data processing I first provided a theoretical overview of Standardised Approach that is based on external ratings from credit rating agencies and therefore, is less risk sensitive method to quantification of credit risk capital requirement. As a part of the chapter I also provide a steps that lead to the amount of capital requirement under this approach.

Next, I discuss the second regulatory method – IRB – that is further divided into foundation IRB and advanced IRB. Advantage of IRB approach in comparison to standardised stem from possibility of internal modelling of parameters used in the formula. The thesis employs the foundation method to determine capital requirements where the bank is allowed to model probability of default. Therefore, I performed variables selection and suggested a model based on accounting information employing logistic regression that was further validated on its discriminatory power. The final model did not allowed me to prove the second stated hypothesis about superiority of solvency ratios to other groups of financial ratios in bankruptcy prediction. Based on the estimated PDs I set an internal rating system that was using so called cohort method tested on calibration. In other words, how well the model fits the true historical PDs. I founded out that the rating system is not in line with historical PDs. It rather overestimates the default probabilities. With this issue in mind I used the rating system in the quantification of capital requirements. Moreover, I proposed another internal rating system that was based on S&P's transition matrix and also used to determine capital requirements.

With the proposed rating systems and determination of further necessary parameters I quantified credit risk capital requirements also under FIRB approach. With the outcomes in hand from both methods I could prove the first hypothesis that using more sophisticated regulatory models banks reach lower capital requirements despite the inappropriate internal rating system in terms of calibration as it overestimates the PDs which implies the higher capital requirements than the ones that would be reached with more accurate rating system. This issue also caused lower capital requirements based on S&P's rating system in comparison to logit rating system. I would expect the opposite result as the rating system derived from regression model should be more risk sensitive than S&P's external ratings and therefore, provide a lower capital requirement.

To my best knowledge, the research on quantification of capital requirements to credit risk is not so extended. Therefore, I consider this thesis as a useful tool providing a deeper insight into possible credit risk management methods. It can serve as a basis for further studies that can improve it by e.g. applying more sophisticated and specific portfolio, performing the determination of the overall capital requirements to credit,

market and operational risk or the cooperation with some bank may enhance this type of study.

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Annex 1

Originally selected variable description:

- **x1=Total Liabilities/Total Equity**

So called Debt to equity ratio is an indicator measuring financial leverage, the ratio indicates how much debt a firm uses to finance its assets relative to the amount of value represented in equity. The higher the ratio, the higher debt levels, which generally indicates that the firm is more risky.

Negative debt to equity ratio caused by negative amount of equity can indicate a red flag. It can be interpreted as if all assets are sold and all debts are paid remaining negative amount is owed by the owners. Nevertheless, common stockholders are prevented from facing actual liability according to the structure publicly traded corporations. The firm needn't to be able to operate under these conditions for a long time. On the other hand, negative equity can be, for instance, caused by accounting approaches used to deal with accumulated losses from prior years. Generally, these accumulated losses are perceived as liabilities carried forward until future release and the firm is despite that fact able to maintain its operations as the losses oftentimes exist only on paper.

In our case we incline to the first explanation as the majority of negative equities relates to firms which are assigned as defaulted ones.

- **x2=Total Liabilities/Total Assets**

Total liabilities to total assets ratio is another from the class of leverage ratios. It measures the total amount of debt relative to the assets. Higher ratio indicates higher degree of leverage, and thus, higher degree of company's financial risk.

- **x3=(Net Income + Depreciation)/Total Liabilities**

The ratio represents the ability of a firm to meet its long term debt. It also provides an evaluation of the firm's likelihood to continue gathering its debt obligations. The ratio is considered to be industry specific. Nevertheless, as a general rule of thumb, the ratio

bigger than 20% is deemed to be financially sound. Therefore in general, lower ratio reflects increased probability of the firm being on default with its debt obligations.

- **x4=EBIT/Interest Expense**

So called interest coverage ratio represents how easily a firm can pay interest on an outstanding debt. It is another solvency ratio which plays an important role in the return for shareholders. As soon as firm faces problems with paying interests, it may leads to further borrowing or dipping into firm's cash. With lower interest coverage ratio the firm is burdened with more debt expenses. Generally, the potential breaking point could be 1,5. Ratio lower than 1,5 may indicate questionability of firm's ability to meet its interest expenses. This can affect lenders' willingness to lend the firm more money, as the firm's default risk seems to be too high. In case of large corporations, they usually have high interest coverage ratio. It is important to take into account that this ratio is highly variable when measuring firms among various industries.

In case of a negative ratio which is caused by negative EBIT, it implies that the firm is dependent on existing cash reserves to pay its interest.

- **x5=Sales/Inventories**

So called inventory turnover is a measurement of how many times a firm's inventory is sold and replaced over a period. When the ratio is low, it can be an indicator of inefficiency, since inventory usually has a rate of return of zero. Between other signals of low turnover ratio belong, for instance, poor liquidity, possible overstocking, and obsolescence. On the other hand, it can also reflect a planned inventory buildup in the case of anticipation of quickly increasing prices or in the case of material deficiencies. When the ratio is high, it can be a signal of either strong sales or ineffective buying. It can be an indicator of better liquidity on the one hand. On the other hand, it can be a signal of lack of or inadequate levels of inventory, which may result in a loss in business.

- **x6=Sales/Total Assets**

So called asset turnover ratio represents the value of a firm's sales generated relative to the value of firm's assets. The ratio can indicate the efficiency with which a firm

allocates its assets to generate revenue. In general, higher asset turnover ratio is a signal of firm's better performance, as increased ratio denotes that the firm generates more revenue per dollar of assets. We should take into account that the ratio is industry specific, therefore, it is not appropriate to compare the ratio across various industries.

- **x7=Acc.Receivables*365/Sales**

Financial ratio called accounts receivable collection period or days sales outstanding represents a comparison of the receivables to the sales activity of a firm. It is used to assess how long customers are taking to pay a firm. The lower the value of the ratio, the less firm's funds in accounts receivable is locked up, and therefore, the funds can be used for other purposes. Moreover, decreased period of time when receivables remain unpaid indicates less risk of defaulted payment by customers.

- **x8=Net Income/Sales**

So called net profit margin ratio is considered to be a key financial indicator used to evaluate firm's profitability. Generally, the financial ratio measures how much of each dollar gained by the firm is transferred into profits. Therefore, it indicates the firm's efficiency as well as how well it can control its costs. The higher the net profit margin is, the more effective the firm is able to convert revenues into actual profit. In case of negative margin firm does not earn enough to cover its expenses. The ratio should be used only to compare firms within the same industry.

- **x9=Net Income/Shareholders' equity**

The financial ratio called Return on Equity (ROE) is a profitability ratio measuring how much profit a firm generates with the money invested from shareholders. ROE is a ratio important from the investors' point of view, not the firm, as it is used to assess how much money is earned based on the investments from the investors in the firm, not the firm's investment in assets, for instance. Generally, the higher the ratio, the better, as it indicates that the firm uses its investors' funds effectively. However, the comparison of ROE should be made within the same industry.

- **x10=Net Income/Total Assets**

So called Return on Assets (ROA) ratio indicates a firm's profitability relative to its total assets. ROA represents the efficiency of using firm's assets to generate earnings. It can be also interpreted as firm's ability to generate profit before leverage, rather than by exploiting leverage. It makes sense to compare firms within the same industry as various industries can use assets in a different way.

- **x11=Retained Earnings/Total Assets**

Retained earnings ratio serves as a measure of the firm's ability to accumulate earnings using its assets. The financial ratio reflects the size of the firm's leverage. In other words, firms with low ratio finance their capital expenditures through borrowings rather than through retained earnings which can indicate that the firm is more risky. Therefore, the higher the ratio is, the better, as it indicates that the firm is able to retain more earnings. Also in this case, it is recommended to compare the ratio within the same industry.

- **x12=Current Assets/Current Liabilities**

So called current ratio is used as an indicator of firm's ability to meet its short term debt obligations. It represents whether or not a firm is able to pay its debts over the next 12 months. The higher the ratio, the more the firm is liquid. However, it does not essentially have to be a good sign. On the one hand, low values are a result of that a firm may have difficulty to meet its current obligations. Nevertheless, to get a better sense of the firm's liquidity the investor should take into account its operating cash flow as the decreased ratio can be fostered by a strong operating cash flow. On the other hand, too high values of current ratio may indicate that the firm does not use its current assets or its short term financing facilities efficiently. In general, it is considered that high current ratio is better than the low one as the firm is more likely to meet its short term liabilities.

- **x13=(Current Assets – Inventories)/Current Liabilities**

The ratio known as a Quick Ratio is used as a measure whether the firm is able to meet its short term obligations using its most liquid assets. Therefore, the inventories are deducted from the current assets, because it usually needs time to convert inventories into cash and when they have to be sold as soon as possible, the firm may have to adopt

lower price than the book value of the inventories. Quick ratio is a signal for creditors how much of the firm's short term debt can be satisfied by selling all the firm's liquid assets at very short time. When the ratio is less than one, it implies that the firm is not currently able to pay back its current obligations, which can be a bad signal for investors.

- **x14=Cash and Cash Equivalents/Current Liabilities**

So called cash ratio is a refinement of already mentioned quick ratio. It represents to which extend can readily available funds pay off current liabilities. The cash ratio is considered to be the most conservative and stringent of three liquidity ratios – cash, quick and current ratio – as it only takes into account the firm's most liquid short term assets that can be most easily used to repay current debt. As in the case of current ratio, to high values does not have to be a good sign, because it may reflect poor asset utilization for a firm keeping large amounts of cash on its balance sheet.

- **x15=Working Capital/Total Assets**

Working Capital is defined as Current Assets – Current Liabilities. Working capital to Total Assets ratio belongs also to the group of liquidity ratios. Owners and managers of the firm are interested in this ratio, because it is an indicator of possible lack of funds to continue business operations. Usually an increasing ratio is a positive signal, indicating the firm's liquidity is enhancing over time. On the other hand, decreasing or negative ratio reflects that the firm may hold too many current liabilities that is not able to cover.

Annex 2

Standardised approach and capital requirements quantification:

Firm	Year	Rating S&P	Loans in EUR mill.	Days overdue	Allowance in EUR mill.	Exposure	Risk Weight	RWA	RWA*8%
Coca-Cola Company	2015	AA	5	-998	0	5	20%	1	0
L'Oreal SA	2015	AA	13	-285	0	13	20%	3	0
East Japan Railway Company	2015	AA-	200	-325	0	200	20%	40	3
NIKE, Inc. Class B	2015	AA-	18	-213	0	18	20%	4	0
Novo Nordisk A/S Class B	2015	AA-	21	-585	0	21	20%	4	0
Novozymes A/S Class B	2015	AA-	42	-369	0	42	20%	8	1
NTT DoCoMo, Inc.	2015	AA-	12	-574	0	12	20%	2	0
adidas AG	2015	A+	15	-759	0	15	50%	8	1
BASF SE	2015	A+	31	-1099	0	31	50%	15	1
GlaxoSmithKline plc	2015	A+	46	-940	0	46	50%	23	2
Honda Motor Co., Ltd.	2015	A+	290	-561	0	290	50%	145	12
Intel Corporation	2015	A+	101	-1093	0	101	50%	50	4
NTT DATA Corporation	2015	A+	74	-201	0	74	50%	37	3
Geberit AG	2015	A	210	-907	0	210	50%	105	8
Kuraray Co., Ltd.	2015	A	435	-854	0	435	50%	218	17
Baxter International Inc.	2015	A-	50	-268	0	50	50%	25	2
Centrica plc	2015	A-	340	-475	0	340	50%	170	14
Daikin Industries, Ltd.	2015	A-	26	-437	0	26	50%	13	1
Diageo plc	2015	A-	13	-496	0	13	50%	7	1
Danone SA	2015	A-	63	-844	0	63	50%	32	3
Mitsubishi Heavy Industries, Ltd.	2015	A-	660	-954	0	660	50%	330	26
Neste Corporation	2015	A-	710	-469	0	710	50%	355	28
Atlantia S.p.A	2015	BBB+	85	-47	1	85	100%	85	7
LM Ericsson Telefon AB Class B	2015	BBB+	58	-72	1	58	100%	58	5
Hochtief AG	2015	BBB+	439	-210	4	435	100%	435	35
Kesko Oyj Class B	2015	BBB+	29	-31	0	28	100%	28	2
Compagnie Generale des Etablissements Michelin SC	2015	BBB+	260	-153	3	257	100%	257	21
Encana Corporation	2015	BBB	23	49	0	23	100%	23	2

Encana Corporation	2015	BBB	23	49	0	23	100%	23	2
Hewlett Packard Enterprise Co.	2015	BBB	200	-4	2	198	100%	198	16
Iberdrola SA	2015	BBB	214	15	2	212	100%	212	17
Lafarge SA	2015	BBB	351	-28	4	347	100%	347	28
Nippon Yusen Kabushiki Kaisha	2015	BBB	402	-48	4	398	100%	398	32
Accor SA	2015	BBB-	61	43	1	61	100%	61	5
Fresenius Medical Care AG & Co. KGaA	2015	BBB-	86	-93	1	85	100%	85	7
Acciona SA	2015	BB+	36	-15	1	35	100%	35	3
Dell Inc.	2015	BB+	74	10	2	72	100%	72	6
Nokia Oyj	2015	BB	50	23	1	49	100%	49	4
Cable & Wireless Communications Plc	2015	BB-	62	12	2	61	100%	61	5
Lonmin Plc	2015	BB-	26	43	1	26	100%	26	2
Air France-KLM SA	2015	B+	196	64	10	186	150%	279	22
Alpha Natural Resources, Inc.	2015	D	1 056	329	1 056	0		0	0
BG Group plc Sponsored ADR	2015	NR	139	3	21	119	100%	119	9

CR=	354 EUR mill.

Exposure at default -> Days overdue>90	
Allowance > 20%	RW 100%
Allowance < 20%	RW 150%

Annex 3

[a] FIRB approach and capital requirements quantification using internal rating system derived from logit model:

Firm	Year	PD logit	LGD	EAD	Asset correlation R	scaling factor	Confidence	Maturity adjustment (b)	Maturity (M)	Maturity input	K(PD,LGD,M)	RWA	CR (in mill EUR)
Acciona SA	2015	2,02%	45%	35	0,1637	1,06	99,9%	0,11040704	2,5	1,2	0	43	3
Accor SA	2015	2,02%	45%	61	0,1637	1,06	99,9%	0,11040704	2,5	1,2	0	74	6
adidas AG	2015	0,23%	45%	15	0,2270	1,06	99,9%	0,20367176	2,5	1,4	0	8	1
Air France-KLM SA	2015	0,19%	45%	186	0,2291	1,06	99,9%	0,21322791	2,5	1,5	0	84	7
Atlantia S.p.A	2015	0,35%	45%	85	0,2207	1,06	99,9%	0,1834413	2,5	1,4	0	53	4
BASF SE	2015	0,04%	45%	31	0,2376	1,06	99,9%	0,29934165	2,5	1,8	0	6	0
Baxter International Inc.	2015	0,07%	45%	50	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	13	1
BG Group plc Sponsored ADR	2015	0,02%	45%	119	0,2388	1,06	99,9%	0,34233246	2,5	2,1	0	14	1
Cable & Wireless Communications Plc	2015	1,03%	45%	61	0,1917	1,06	99,9%	0,13628796	2,5	1,3	0	60	5
Centrica plc	2015	2,02%	45%	340	0,1637	1,06	99,9%	0,11040704	2,5	1,2	0	415	33
Coca-Cola Company	2015	0,01%	45%	5	0,2394	1,06	99,9%	0,38820681	2,5	2,4	0	0	0
Daikin Industries, Ltd.	2015	0,19%	45%	26	0,2291	1,06	99,9%	0,21322791	2,5	1,5	0	12	1
Dell Inc.	2015	0,02%	45%	72	0,2388	1,06	99,9%	0,34233246	2,5	2,1	0	9	1
Diageo plc	2015	0,15%	45%	13	0,2313	1,06	99,9%	0,22535476	2,5	1,5	0	5	0
East Japan Railway Company	2015	0,19%	45%	200	0,2291	1,06	99,9%	0,21322791	2,5	1,5	0	91	7
Encana Corporation	2015	19,45%	45%	23	0,1200	1,06	99,9%	0,04335247	2,5	1,1	0	58	5
LM Ericsson Telefon AB Class B	2015	0,04%	45%	58	0,2376	1,06	99,9%	0,29934165	2,5	1,8	0	11	1
Fresenius Medical Care AG & Co. KGaA	2015	0,19%	45%	85	0,2291	1,06	99,9%	0,21322791	2,5	1,5	0	38	3
Geberit AG	2015	0,02%	45%	210	0,2388	1,06	99,9%	0,34233246	2,5	2,1	0	25	2
GlaxoSmithKline plc	2015	0,35%	45%	46	0,2207	1,06	99,9%	0,1834413	2,5	1,4	0	28	2
Danone SA	2015	0,11%	45%	63	0,2336	1,06	99,9%	0,24177454	2,5	1,6	0	21	2

Hewlett Packard Enterprise Co.	2015	0,15%	45%	198	0,2313	1,06	99,9%	0,22535476	2,5	1,5	0	79	6
Hochtief AG	2015	1,03%	45%	435	0,1917	1,06	99,9%	0,13628796	2,5	1,3	0	430	34
Honda Motor Co., Ltd.	2015	0,04%	45%	290	0,2376	1,06	99,9%	0,29934165	2,5	1,8	0	53	4
Iberdrola SA	2015	0,11%	45%	212	0,2336	1,06	99,9%	0,24177454	2,5	1,6	0	70	6
Intel Corporation	2015	0,01%	45%	101	0,2394	1,06	99,9%	0,38820681	2,5	2,4	0	8	1
Kesko Oyj Class B	2015	0,47%	45%	28	0,2149	1,06	99,9%	0,16986874	2,5	1,3	0	20	2
Kuraray Co., Ltd.	2015	0,15%	45%	435	0,2313	1,06	99,9%	0,22535476	2,5	1,5	0	173	14
Lafarge SA	2015	0,23%	45%	347	0,2270	1,06	99,9%	0,20367176	2,5	1,4	0	174	14
Lonmin Plc	2015	58,51%	45%	26	0,1200	1,06	99,9%	0,02186866	2,5	1,0	0	52	4
L'Oreal SA	2015	0,23%	45%	13	0,2270	1,06	99,9%	0,20367176	2,5	1,4	0	7	1
Compagnie Generale des Etablissemer	2015	0,19%	45%	257	0,2291	1,06	99,9%	0,21322791	2,5	1,5	0	116	9
Mitsubishi Heavy Industries, Ltd.	2015	0,15%	45%	660	0,2313	1,06	99,9%	0,22535476	2,5	1,5	0	262	21
Neste Corporation	2015	0,35%	45%	710	0,2207	1,06	99,9%	0,1834413	2,5	1,4	0	442	35
NIKE, Inc. Class B	2015	0,11%	45%	18	0,2336	1,06	99,9%	0,24177454	2,5	1,6	0	6	0
Nippon Yusen Kabushiki Kaisha	2015	0,59%	45%	398	0,2093	1,06	99,9%	0,15975605	2,5	1,3	0	316	25
Nokia Oyj	2015	0,07%	45%	49	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	12	1
Novo Nordisk A/S Class B	2015	0,07%	45%	21	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	5	0
Novozymes A/S Class B	2015	0,23%	45%	42	0,2270	1,06	99,9%	0,20367176	2,5	1,4	0	21	2
NTT DATA Corporation	2015	0,47%	45%	74	0,2149	1,06	99,9%	0,16986874	2,5	1,3	0	53	4
NTT DoCoMo, Inc.	2015	0,01%	45%	12	0,2394	1,06	99,9%	0,38820681	2,5	2,4	0	1	0
Alpha Natural Resources, Inc.	2015	58,51%	45%	0	0,1200	1,06	99,9%	0,02186866	2,5	1,0	0	0	0
												CR=	270 mill EUR

[b] FIRB approach and capital requirements quantification using internal rating system based on S&P's transition matrix:

Firm	S&P's rating	Year	PD S&P's	LGD	EAD	Asset correlation R	scaling factor	Confidence	Maturity adjustment (b)	Maturity (M)	Maturity input	K(PD,LGD,M)	RWA	CR (in mill EUR)
Acciona SA	BB+	2015	0,37%	45%	35	0,2197	1,06	99,9%	0,18084297	2,5	1,4	0	22	2
Accor SA	BBB-	2015	0,28%	45%	61	0,2243	1,06	99,9%	0,19406164	2,5	1,4	0	34	3
adidas AG	A+	2015	0,06%	45%	15	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	4	0
Air France-KLM SA	B+	2015	2,20%	45%	186	0,1599	1,06	99,9%	0,10732145	2,5	1,2	0	233	19
Atlantia S.p.A	BBB+	2015	0,12%	45%	85	0,2330	1,06	99,9%	0,23710984	2,5	1,6	0	30	2
BASF SE	A+	2015	0,06%	45%	31	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	7	1
Baxter International Inc.	A-	2015	0,07%	45%	50	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	13	1
BG Group plc Sponsored ADR	NR	2015	0,03%	45%	119	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	18	1
Cable & Wireless Communications Plc	BB-	2015	1,05%	45%	61	0,1910	1,06	99,9%	0,13551123	2,5	1,3	0	60	5
Centrica plc	A-	2015	0,07%	45%	340	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	87	7
Coca-Cola Company	AA	2015	0,02%	45%	5	0,2388	1,06	99,9%	0,34233246	2,5	2,1	0	1	0
Daikin Industries, Ltd.	A-	2015	0,07%	45%	26	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	7	1
Dell Inc.	BB+	2015	0,37%	45%	72	0,2197	1,06	99,9%	0,18084297	2,5	1,4	0	46	4
Diageo plc	A-	2015	0,07%	45%	13	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	3	0
East Japan Railway Company	AA-	2015	0,03%	45%	200	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	31	2
Encana Corporation	BBB	2015	0,18%	45%	23	0,2297	1,06	99,9%	0,215972	2,5	1,5	0	10	1
LM Ericsson Telefon AB Class B	BBB+	2015	0,12%	45%	58	0,2330	1,06	99,9%	0,23710984	2,5	1,6	0	20	2
Fresenius Medical Care AG & Co. KGaA	BBB-	2015	0,28%	45%	85	0,2243	1,06	99,9%	0,19406164	2,5	1,4	0	47	4
Geberit AG	A	2015	0,06%	45%	210	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	49	4
GlaxoSmithKline plc	A+	2015	0,06%	45%	46	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	11	1
Danone SA	A-	2015	0,07%	45%	63	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	16	1

Hewlett Packard Enterprise Co.	BBB	2015	0,18%	45%	198	0,2297	1,06	99,9%	0,215972	2,5	1,5	0	87	7
Hochtief AG	BBB+	2015	0,12%	45%	435	0,2330	1,06	99,9%	0,23710984	2,5	1,6	0	152	12
Honda Motor Co., Ltd.	A+	2015	0,06%	45%	290	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	67	5
Iberdrola SA	BBB	2015	0,18%	45%	212	0,2297	1,06	99,9%	0,215972	2,5	1,5	0	93	7
Intel Corporation	A+	2015	0,06%	45%	101	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	23	2
Kesko Oyj Class B	BBB+	2015	0,12%	45%	28	0,2330	1,06	99,9%	0,23710984	2,5	1,6	0	10	1
Kuraray Co., Ltd.	A	2015	0,06%	45%	435	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	101	8
Lafarge SA	BBB	2015	0,18%	45%	347	0,2297	1,06	99,9%	0,215972	2,5	1,5	0	152	12
Lonmin Plc	BB-	2015	1,05%	45%	26	0,1910	1,06	99,9%	0,13551123	2,5	1,3	0	26	2
L'Oreal SA	AA	2015	0,02%	45%	13	0,2388	1,06	99,9%	0,34233246	2,5	2,1	0	2	0
Compagnie Generale des Etablissemer	BBB+	2015	0,12%	45%	257	0,2330	1,06	99,9%	0,23710984	2,5	1,6	0	90	7
Mitsubishi Heavy Industries, Ltd.	A-	2015	0,07%	45%	660	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	168	13
Neste Corporation	A-	2015	0,07%	45%	710	0,2359	1,06	99,9%	0,2667366	2,5	1,7	0	181	14
NIKE, Inc. Class B	AA-	2015	0,03%	45%	18	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	3	0
Nippon Yusen Kabushiki Kaisha	BBB	2015	0,18%	45%	398	0,2297	1,06	99,9%	0,215972	2,5	1,5	0	175	14
Nokia Oyj	BB	2015	0,62%	45%	49	0,2080	1,06	99,9%	0,15759155	2,5	1,3	0	39	3
Novo Nordisk A/S Class B	AA-	2015	0,03%	45%	21	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	3	0
Novozymes A/S Class B	AA-	2015	0,03%	45%	42	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	6	1
NTT DATA Corporation	A+	2015	0,06%	45%	74	0,2365	1,06	99,9%	0,27553036	2,5	1,7	0	17	1
NTT DoCoMo, Inc.	AA-	2015	0,03%	45%	12	0,2382	1,06	99,9%	0,31683442	2,5	1,9	0	2	0
Alpha Natural Resources, Inc.	D	2015	100,00%	45%	0	0,1200	1,06	99,9%	0,01404699	2,5	1,0	0	0	0
													CR=	172 mill EUR