

**UNIVERZITA KARLOVA V PRAZE**

**FAKULTA SOCIÁLNÍCH VĚD**

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*Magisterská práce*

**Financial Risk and Models of its Measurement:  
Altman's Z-score Revisited**

Praha 2011

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Akademický rok: 2010/2011

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## ***Abstract***

Master thesis touches upon the interesting spheres of risk classification, measurement and management of financial institutions. Modern banks have numerous credit risk measurement models at their disposal. However, agreement about performance of those models is not that unanimous and to some point the models are blamed for breaking out of 2007 financial crisis. In the theoretical part of the thesis we provide survey of risk measurement practices in banks. We investigate the main types of risk of banks in their day-to-day activities. Special focus is paid on the credit risk and on the models and techniques of its measurement; Practical part of thesis then contains construction and accuracy estimation of particular credit-risk-model (Altman Z-score). In it we construct and compute Altman Z-score for sample of firms from two chosen sectors in United Kingdom. Main goals of the work are a) testing accuracy of the model by comparing its outputs to real development, and b) econometric testing of the specification of the model itself.

## ***Abstrakt***

Magisterská práce se věnuje tématu klasifikace, měření a řízení rizika finančních institucí. V dnešní době mají banky k dispozici množství modelů pro měření a řízení finančních rizik. Co se však týká názorů na jejich výkonnost, nepanuje jednotná shoda. Jejich nedostatečná schopnost zachytit a hodnotit skutečné riziko bývá někdy dokonce uváděna jako jedna z příčin propuknutí finanční krize v roce 2007. V teoretické části diplomové práce podáváme přehled o hlavních, bankami používaných, metodách měření rizika. Hlavní pozornost klademe na úvěrové riziko a techniky jeho měření. Praktická část práce se pak věnuje konkrétnímu modelu měření úvěrového rizika (Altmanovu Z-skóre). V této části konstruujeme a hodnotíme Altmanovo Z-skóre pro firmy z vybraných sektorů Velké Británie z období 2004 – 2008. Hlavními cíli diplomové práce jsou a) hodnocení přesnosti modelu porovnáním jeho výstupů se skutečným vývojem a b) ověřování ekonometrických vlastností specifikace samotného modelu.

**Keywords:** risk, risk measurement, value at risk, credit risk, market risk, risk exposure, risk exposure.

### ***Poděkování***

Na tomto místě bych rád poděkoval panu Prof. Ing. Michalu Mejstříkovi CSc. za jeho odbornou pomoc a cenné rady při psaní této diplomové práce.

Také bych chtěl poděkovat Mgr. Svatoplukovi Svobodovi a PhDr. Ludmile Stakchovich za přínosné připomínky a návrhy.

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***List of Abbreviations***

BIS	Bank of International Settlement
CMR	Cumulative mortality rate
CNB	Czech National Bank
EAD	Exposure at default
ECB	European Central Bank
FSR	Financial Stability Report
GDP	Gross domestic product
LGD	Loss given default
LSE	London Stock Exchange
MMR	Marginal mortality rate
NAIC	National Association of Insurance Commissioners
NPV	Net present value
OCC	Office of the controller of the currency
ORX	Operational Riskdata Exchange Association
PD	Probability of default
SR	Survival rate
VaR	Value at risk

## ***Introduction***

Risk is a fundamental element which has a great influence the behavior of financial institution. That is why, with the increase in level of global integration, geography, complexity and diversity of activities of international financial institutions, a lot of attention is being paid to the risk management practice in these organizations on different levels.

Despite the whole complexity of the process, definition of the risk management is quite straightforward: *“the identification, assessment, and prioritization of risk followed by coordinated and economical application of resources to minimize, monitor, and control the probability and/or impact of unfortunate events or to maximize the realization of opportunities”* (Alberts 2008, p.67). In other words risk management is the process of getting the right information, at the right time to the right people, such that those people can make the most informed judgment possible.

The issues of the risk management in financial institutions in general and in banks in particular are of great importance and interest also due to 2007 financial crisis: the shortcomings in the risk measurement and assessment methods (which is a part of a risk management process), in particular the credit risk assessment models, are considered to be one of the reasons of the greatest recession since the Great Depression.

These drawbacks indicate the fact that risk measurement tools, most commonly used worldwide, were unable to model the harsh real and financial shocks. The shortcomings of both traditional and modern risk measurement models are caused by technical restraints, including the fact that the quantitative techniques, which would be analyzed later, are backward-oriented. Hence those models use historical data as a framework for analysis, implicitly assuming that future development of given trends would follow patterns from the past, which is not always the case. Another example of technical limitation is the fact that many hedges are far from being perfect, which gives the rise to a basis risk, e.g. when historical correlation, or default rates or any other parameters of the model deviate from the modeled outcomes, which in the worst case scenario may cause losses and even default of the subject.

In this paper we are first of all interested in analyzing types of risk that financial institutions are exposed to. There are various classifications of risks – some of which were proposed by regulators and supervisory bodies, the others by banks themselves. We are

interested in taking a closer look at how particular risks influence activities of banks.

Secondly we discuss credit risk, as one of the most inherent in financial sector; and historical evolution of credit risk measurement techniques as well. This issue is quite interesting because by examining the development of risk measurement models we are able to see how subjective they were at their very beginning and how sophisticated they have become.

The aim of this Master thesis is to present a closer look into the interesting area of credit risk measurement models. This work mainly focuses on the evaluation of the reliability of credit risk measurement models (in particular Altman Z-score model). The research can provide new, rather important findings for both banks and firms. Banks are exposed to the credit risk, whereas firms are source of that risk.

Our analysis is performed on the sample of 25 United Kingdom companies, which operate/operated in the construction and materials sector. Some of the entities went bankrupt and some are still operating on the market. Firstly we will try to examine if Altman Z-score model, whose sole purpose is to predict possible bankruptcies, would be able to distinguish between failed and non-failed companies and predict failures of those which bankrupted.

Secondly, within the Altman Z-score model, we will try to determine if the variables used are jointly significant for determination of the final score, as well as significance of every single variable in explaining the variation of the final outcome.

The issues of credit risk measurement are well covered by theoretical literature (Saunders 2002; Abrahams 2009; Trueck 2009). Although the majority of publications and research done by academicians, practitioners and regulators touches upon the VaR methodology, they live aside modern developments in this field, such as macroeconomic simulations and insurance approach.

The Master thesis is organized in the following way. In the first chapter, we will begin with theoretical discussion, presenting brief analysis of the main types of risk that modern financial system is nowadays facing.

Chapter two will introduce both traditional and modern approaches to credit risk measurement. We will analyze most commonly used credit risk measurement techniques, their pros and cons.

Chapter three will present empirical example of the credit risk measurement model estimation. Here we will construct and evaluate prediction ability of the Altman Z-score model as well as examine significance of explanatory variables of the model. Our aspiration is also examine how well Altman Z score model is able to foresee real bankruptcies in observed construction sector in UK during period 2004-2008.

In the conclusion, we will summarize major facts on risk types and risk measurement in practices of banks, as well as the result of our analysis on Altman's Z-score model testing. We will also try to conclude on the effectiveness of using such models.

## ***Chapter 1. Theoretical Framework: Classification and brief analysis of risks in financial sector***

*“The first step in the risk management process is to acknowledge the reality of risk”.*

*- Author: Unknown*

Financial institutions, including banks, by definition operate in the risky environment. With an increasing competition and rapidly changing operational environment, which influences economic potential of the companies, banks all over the Globe are facing different types of financial and non-financial risks.

In a general risk management theory risks, which banks facing, are divided into two generalized categories: **business risks** and **control risks** (Sagrove 2007). Business risk *“arises from operational activities of financial institutions and includes the following types of risks: capital, credit, market, earnings, liquidity, business strategy and environmental, operational and group risk”* (Spedding and Rose 2008).

*“Control risk is the type of risks which arises due to poor management systems and incorporates compliance risk, internal control, management and organizational risk”* (Spedding and Rose 2008). Control risks could be characterized as highly interdependent, which means that increase in the level of exposure to one of the risks always causes increase in possibility of arising of other risks. In this respect we would like to mention that risks of control are an issue of corporate governance and they would not be touched upon in this Master thesis.

On the other hand, Basel Committee on Bank Supervision in its capital accord identifies only three main categories of risks: **credit risk**, **market risk** and **operational risk** (BIS 1999). The reason for such a distinction between academic classification and regulator’s point of view is quite simple: Basel 2 identifies these 3 types of risks as the major loss factors for the financial institutions, (which is of major importance from regulatory point of view). In the following Master thesis we follow the classification of risks introduced in the capital accord.

The following chapter is based on the studies of Gallati (2003), Van Greuning and

Bratanovic (2007), Papaioannou (2006), Saunders and Allen (2007) and a number of consultative papers of BIS and ECB.

## **1.1 Credit risk**

### **1.1.1 General characteristic**

There are several definitions of the credit risk. The most appropriate to the topic of this Master thesis was proposed by the Basel committee on banking supervision: “*credit risk is the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with agreed terms*” (BIS 2000, p.5). Credit risk arises every time when a borrower is expecting to use future cash flows to pay out current obligation. Increase in exposure to the credit risk causes liquidity imbalance, which in its turn results in insolvency or even bankruptcy of the entity.

Main task of credit risk management is to force financial institutions to recover, assess, actively manage and optimize their credit risk exposure at both individual and portfolio levels using appropriate models and techniques.

Credit risk models are intended to aid banks in quantifying, aggregating and managing risks across geographical and product lines. The outputs of these models play increasingly important roles in bank’s risk management and performance measurement processes, customer profitability analysis, risk-based pricing, active portfolio management and capital structure decisions.

Main issue in operationalizing the credit risk assessment is the data limitation. The absolute majority of credit instruments are not subject of trade on the marked to market, which implies information limitations regarding their prices and other parameters. The reason for shortage of data that are important for performing valuation lies also in the infrequent nature of the default events and the long-term horizon of the instruments.<sup>1</sup> It means that in order for credit risk models to maintain their accuracy it is necessary to use simplifying assumptions and relevant data sources. However simplifying assumptions increase the degree of uncertainty and biasness in the model. This in turn increases chance that estimation results will be inconsistent.

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<sup>1</sup> The default events are more infrequent in comparison with fluctuations in the market prices.

### **1.1.2 Key principles of credit risk management**

The key principles of sound credit risk management may differ from institution to institution. There are certain general recommendations however, which were developed jointly by the regulators and practitioners and form a framework for optimal credit risk assessment and management practices.

First one is the **introduction of appropriate credit risk environment**, which involves two steps (BIS 1999):

- Development, implementation and revision of credit risk strategy and other important risk policies by senior management and board. In order to keep the risk exposure on the appropriate level, credit risk strategy has to be revised and reapproved periodically. In the best case scenario credit risk strategy mirrors or is very tightly linked to the level of profitability of the financial institution;
- Implementation of strategies and procedures developed and approved on the previous step, which are involved in identifying, measuring, monitoring and controlling credit risk.

These policies should be implemented within the context of such factors as market position, trade area, staff capabilities and technology. So, basis for an effective credit risk management process is identification of existing and potential risks, inherent in any product or activity (Gallati 2003). Consequently, it is important for banks to identify all credit risks inherent in all the products they offer and in the activities they are engaged in. Such identification stems from a careful review of the credit risk characteristics of product or activity (BIS 1999).

Second cornerstone is **operating under clear and sound credit granting process**. It means having a clear and risk weighted credit risk measurement criteria, which include a thorough knowledge about the counterpartys' (borrowers') activities, structure and aim of financing, and sources of repayment of the borrowed funds. It also implies the necessity of having set credit limits both for the individual borrowers and groups. The reason for such limits is an aggregation of different types of exposures in case of interconnected counterparties which could have a negative influence on the overall credit risk exposure on and off the balance sheet.

The third cornerstone is **the necessity for the credit administration, measurement and monitoring process**. Once the risk is undergone, it is crucial to make sure it is properly maintained. This includes keeping track of overall market situation, activities of the counterparty, and general level of the risk exposure as well. All this is possible due to the system of monitoring general composition and quality of the credit portfolio.

Last but not the least is **supervisory duties**. It implies the necessity for the unified system of supervision, which would require credit-risk-takers to identify measure, monitor and control their degree of exposure as a part of the general system of risk management.

## **1.2 Market risks**

*“Market risk is the risk that an entity may experience losses from unfavorable movements in market prices resulting from changes in the price (volatility) of fixed-income instruments, equity instruments, commodities, currencies and related off-balance-sheet contracts”* (Van Greuning and Bratanovic 2009, p. 227).

This type of risk is usually inherent to entire class of assets or liabilities. The reason for that is the notion that the value of the investment may decrease over time due to changes of the market conjuncture or any other event, which may influence the large share of the market (Jorion 2009). Exposure to the market risk increases in the case when banks have an active speculating position on any market (e.g. financial, commodity etc.).

Throughout academic literature (see e.g. Van Greuning and Bratanovic 2009) market risk is frequently addressed as a combination of **foreign exchange risk, interest rate risk, commodities price risk** and **equity position risk**. Let's introduce these types of risk in a bit more detail.

### **1.2.1 Interest rate risk**

*“Interest-rate risk arises from adverse changes in interest rates, causing higher interest costs or lower investment income, and therefore lower profit or even losses”*(Coyle 2001, p.5). Increase in exposure to the interest rate risk is caused by:

- Mismatch between timing of rate changes and timing of cash flows;
- Fluctuations in the changing rate across the various maturities;
- Interest-rate-related options, integrated in the bank services and products.

Thus, changes in the interest rates have a direct impact on the valuation of bank's assets, liabilities and off-balance-sheet items through the changes in the present value of the future cash flows and the volume of the cash flows.

In their practical functioning, banks are exposed to four different "sub-types" of interest rate risk (taken from Coyle 2001):

- **Basis risk** – occurs when yields on assets and costs on liabilities are expressed with the relation to different bases. In certain cases different bases will move at different rates or in different directions. That automatically causes changes in revenues and expenses;
- **Yield curve risk** – the exposure it increases with the increase in the gap between short-term and long-term interest rates. This type of risk usually occurs when bank is operating on the speculative market trying to make a profit by borrowing at lower rates and investing in at higher rates;
- **Mispricing risk** is common for the assets and liabilities, which were over- or under-valued at different times and rates. For example if the loan is funded with fixed rated deposits, the bank's interest margin will fluctuate;
- **Option risk** arises from the option feature of certain financial instruments. The extreme exposure to this risk may influence financial statements and the overall market value of the bank. As a result, bank may not be able to adequately react on the market changes. Due to its nature, option risk is hard to measure and control.

There are various techniques for estimating bank's risk stemming from exposure to the changes in the interest rates. Most of those techniques are sophisticated and yield relevant and unbiased results. The most common of them are calculation of the VaR of the portfolio, estimation of the future multi-period cash flows, accrual income and expenses, stress testing, and marking to market.

### **1.2.2 Exchange rate risk**

Being among the most active participants on the foreign exchange market, banks are extensively exposed to the risk stemming from uncertain movements of exchange rates. Traditional definition of exchange rate risk relates the effect of unexpected exchange rate changes to the value of the firm (Madura 1989). *"Exchange rate risk is defined as the*

*possible direct loss (as a result of an unhedged exposure) or indirect loss in the bank's cash flows, assets and liabilities, net profit and, in turn, its stock market value from an exchange rate move" (Papaioannou 2006, p. 4).*

One of the leading techniques for measurement of the foreign exchange risk exposure is VaR. The essence of the VaR methodology is determination of maximum loss for the given portfolio composition over a given time period with a certain level of confidence. There are number of models for calculation of the value-at-risk. The more widely-used<sup>2</sup> are:

- **Historical simulation** – assumes that future foreign exchange position could be determined using historical data on exchange rates.
- **Variance-covariance modeling** – change in the bank's total foreign exchange position is the composition of changes in the value of the individual foreign exchange position.
- **Monte-Carlo simulation** – principal component analysis of the previous model with the random simulation of components.

The foreign exchange risk management is usually performed through hedging instruments. The most common hedging instruments used by financial institutions are currency forwards and cross-currency swaps. Due to its relative cost efficiency natural hedging is commonly used as an alternative to the instruments of the derivative market. The natural hedging involves such foreign exchange reduction measures as invoicing in the foreign currency, matching foreign currency inflows and outflows in amount and time (Jacque, 1997).

### **1.2.3 Equity price risk**

*"Equity price risk involves potential losses for both on- and off- balance sheet items of banks due to unfavorable fluctuations on the stock market" (Crouhy and Mar, 2006, p. 25).*

Equity price risk may be divided into **general equity price risk**, which involves

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<sup>2</sup> Some of the model for VaR valuation will be discussed in more detail also in the second part of the Master Thesis.

fluctuations on the stock market in general, and **specific price risk**, involving the price fluctuations of the individual stock or subdivision of stocks.

The equity price risk measurement involves assessment of standard deviation of the stock price over a number of periods. The standard deviation will delineate the normal fluctuations one can expect in that particular security, above and below the mean, or average. However, since most investors would not consider fluctuations above the average return as a risk, some economists (e.g. Ieda and Ohba 1999) prefer other means of measuring it (e.g. VaR).

#### **1.2.4 Commodity price risk**

Commodity price risk is commonly referred to as a potential losses occurring as the result of decrease in prices of on- and off-balance sheet items due to unfavorable price fluctuation on the commodity market. Commodity prices indirectly influence bank's credit portfolios by means of increasing or decreasing the market price of the collateral. There is a strong link to the credit risk exposure: increase in the commodity prices decreases the counterparty's ability to repay the loan. Risk management instruments in this case go down to the general historic analyses of the commodity prices and market conjuncture per se. (Blanco, 1998).

### **1.3 Other risks**

Historically, for a long period of time both regulators and practitioners had only been considering credit and market risks to be real threats for financial stability of banks. But since the introduction of Basel 2, which separated operational risk from market and credit risks, general notion has changed. That is why we continue with brief analysis of other critical risk factors: **operational** and **liquidity risk**.

#### **1.3.1 Operational risk**

Major challenge connected to operational risk is its identification. It is hard to believe that until 2004 generally excepted definition of operational risk had been "*everything, which is not under credit or market risk categories*" (Benedek and Homolya 2007, p. 35). It was only in 2004 when BIS developed definitive framework, which afterwards became accepted by financial institutions and regulatory authorities. BIS defined

operational risk as “*the risk of loss resulting from inadequate or failed internal processes, people and systems or from external events*” (BIS 1998, p 3). Alternative approach defines operational risk event as “*An operational risk event is an incident leading to the actual outcome(s) of a business process to differ from the expected outcome(s), due to inadequate or failed processes, people and systems, or due to external facts or circumstances*”(ORX 2007, p.26 ).

Above definitions are a bit broad. BIS and EU therefore present list of particular event categories, classified as operational risk (BIS 2004; EU 2006):

- **Internal (external) fraud** – intentional unauthorized activity, theft or fraud, performed by employee of the bank (in case of external – hacker activity, computer fraud etc.);
- **Employment practice and workplace safety** – employment relations, absence of workplace safety etc.;
- **Business disruption and system failure** – any threats of suffering losses, caused by hardware or software malfunction;
- **Clients, products and business practices** – risk of losses due to private information disclosure, money laundering ets;
- **Damages of physical assets**, caused by natural catastrophes, wars, unauthorized breaches etc.

The above mentioned risk factors put a little more sense in definition of operational risk without touching some of their distinct features, such as its possible endogenous nature. Unlike market and credit risks, increase in operational risk exposure does not cause increase in profit. Therefore banks are only increasing the level of exposure to the risk without being able to compensate for it by the extra profit. More detailed comparison of operational risk, market risk and credit risk is presented in the Table A.1 Appendix 1.

Last but not the least is the operational risk management strategy, developed by BIS and consisting of three major pillars:

- Minimum regulatory capital requirement for operational risk (is determined using three different methodologies, mentioned in capital accord);

- Supervisory review process to enforce a rigorous control environment to limit exposure to capital risk;
- Market discipline requirements.

### **1.3.2 Liquidity risk**

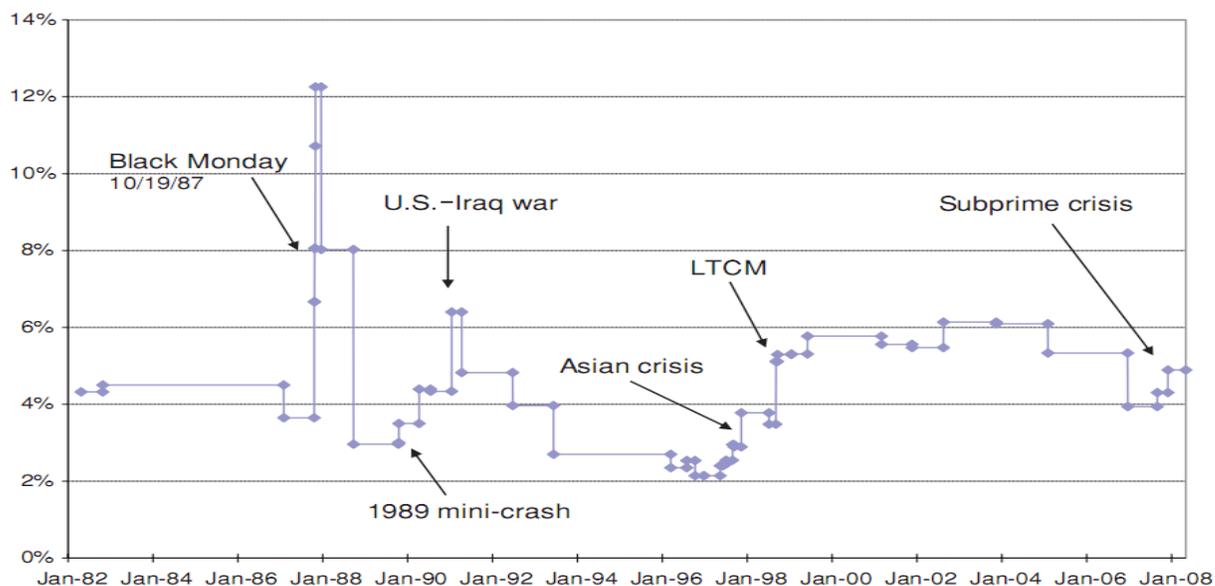
*“Liquidity is the ability of a financial institution to fund increases in assets and meet obligations as they become due”* (BIS 2008, p. 2). Contemporary banks become more and more proactive in fields, which weren't typical for banking before (e.g. financial markets, off-balance sheet operations). Hence, concept of liquidity risk becomes more multi structural. Nowadays, regulatory authorities (e.g. BIS) distinguish between two dimensions of liquidity risk, both of which play certain role in sound risk management practices of banks. Those dimensions are: **funding liquidity risk** and **trading (market) liquidity risk**. Funding liquidity risk is determined by the possibility that over a specific time horizon bank will be unable to meet its immediate obligations (Drehman and Nikolao 2007). Immediate obligations in this case are cash or collateral requirements, capital withdrawals etc. Extent of exposure to funding liquidity risk largely depends on liability structure, reliance on secured sources of funding and access to public markets. According to Drehman (2007), funding liquidity risk has two components: future random in- and outflow of money and future random changes in prices of funding from different sources.

As to trading-related liquidity risk, it is closely connected to market risk and represents losses arising from cost of liquidation of a market position. This type of risk usually occurs in case of imperfect market liquidity during time of financial turmoil. In this case the extent of liquidity varies dramatically depending on the type of market. In case of trading related liquidity risk, losses might be caused by the fact that agents do not receive market price whenever they want to sell the asset. It mostly happens in case of unanticipated market price movements.

If we compare trading-liquidity risk to the market risk (which considers suffering losses due to unfavorable market price movements), we can say that trading-related liquidity risk is more threatening to financial stability of banks due to its unpredictability. Common manifestation of this type of risk is a market slowdown: small number of participants, large transaction costs, and significant margins (Brunnermeier 2008).

Empirically observed correlation between trading liquidity risk and market margins is shown on the Figure 1.1

**Figure 1.1: Margins for S&P 500 futures over the period 1982-2008**



Source: Brunnermeier and Pedersen 2008

The figure above shows margin requirements on S&P 500 futures for members of the Chicago Mercantile Exchange as a fraction of the value of the underlying S&P 500 index multiplied by the size of the contract. Initial or maintenance margins are the same for members. Each dot represents a change in the dollar margin. As we can see from the Figure 1.1 margins did increase during liquidity crises of 1987, 1990 and 2007, which is partially caused by liquidity shocks.

**Quick Note: of the risk measurement in Czech Republic**

*While preparing this Master Thesis we've gone through the number of annual reports of the major banks in the Czech Republic in order to reveal their common risk measurement policies. As we found out, most of the banks only mention certain general notation on how they measure and estimate risks. There were very little if any formal description and explanation of particular models and techniques used in practice. Thus commercial banks in the Czech Republic do use risk measurement models, but in the great extent those are Taylor-made with accordance to need of particular institution.*

*On the other hand, CNB in its periodical FSRs performs stress testing for banking sector of Czech Republic. It also utilizes Stress Index for measuring exposure of Czech banks to six most important risks (stress index was constructed in Geršl and Heřmánek (2008)). In the academic journals there are present numerous studies dedicating to assessing of credit risk in Czech economy and banks. See among others Jakubík and Seidler (2009), Jakubík and Heřmánek (2008), Jakubík (2007), Čihák, Heřmánek and Hlaváček (2007),*

## ***Chapter 2. Credit Risk Measurement: Traditional and Modern Approaches***

As we have already mentioned in the introduction part, **credit risk** measurement has always been crucial for banks' and other financial institutions' functioning. The level of attention to this issue has increased lately not only due to Global Recession, however. Under Basel II accord financial institutions were enabled to calculate regulatory credit-risk capital requirement using internal techniques, which in some cases were based on the probabilities that their counterparties will default. This relative freedom of choice has increased the level of credit risk exposure in case of certain financial institutions because of their inability to distinguish between reliable models. That is the reason why the following part of the Master thesis is devoted to examining most popular credit risk measurement models.

Most of the modern literature (see Drehman and Nikolaos 2007) distinguishes between **traditional** and **modern** models (approaches to credit risk measurement). Traditional techniques of credit risk measurement are specialized on estimation of the probability of default (PD) in an extensive, and at some point subjective manner. They do not take into consideration volatilities in credit quality, which are measured in mark to market models; they do not rely on company's book structure or information from the equity markets, as some contemporary models do. This drawbacks make models vogue and inconsistent from modern dynamic and sophistication point of view. In this part of the Master Thesis we describe four traditional models which are used to estimate the probability of default: **expert systems, artificial neural networks, rating systems and credit scoring models**.

Further analysis will be based on the classical credit risk measurement literature, such as Altman (1968) Stiglitz and Weiss (1981), Allen (2009), Treacy and Carey (2000), Saunders and Allen (2007), Kim and Scott, (1991) and Altman and Saunders (1998) as well as modern papers and consultative documents proposed by the BIS and ECB.

## 2.1 Traditional approaches for measuring credit risk

### 2.1.1 Expert Systems

*“It is probably fair to say that 20 years ago most financial institutions (FIs) relied virtually exclusively on subjective analysis or so-called banker “expert” systems to assess the credit risk on corporate loans” (Altman and Saunders 1998, pp. 1722).*

The essence of the expert system type of model is that determination of probability of default is based upon subjective judgment of the individual, his experience and weights he himself gives to certain key value factors. The more objective values are getting involved only as model’s inputs.

One of the most commonly used expert systems is a so called “**5 C’s**” system. It analyses five factors, which influence creditworthiness of a particular borrower, weights them in a subjective manner and, as a result, reaching an estimate of probability of default (PD). Five factors mentioned above are the following:

- **Character** – analyzes historical performance of the company, e.g. reputation, willingness to take on debt and especially ability to repay it;
- **Capital** – equity side analysis of the company, including a detailed overview of the structure of the equity, major equity holders, base equity based ratios (e.g. debt-to-equity ratio);
- **Capacity** – analyzes ability of the company to meet its obligations relying solely on its earnings;
- **Collateral** – investigation of the assets, financial institution has the right to claim in the event of default of the borrower. The greater the value of the collateral and the higher the priority of bank’s claim, the lower the exposure to suffer losses;
- **Cycle (Macroeconomic) conditions** – examine the dependents of the PD of a potential creditor on the state of the business cycle.

Another critical indicator which could be taken as part of the PD prediction process in expert system models is a level of interest rate. It has been proven (in Stiglitz and Weiss, 1981) that there is a nonlinear dependence between the level of interest rates and expected return on the loans, which could be explained by two phenomena: adverse selection and risk shifting (see Allen, 2009).

Despite the fact that expert systems are still commonly used among practitioners as part of decision making process, their disadvantages are quite obvious: methodology does not give a precise answer on how to choose the relevant factors so that the estimates of PD were as close to the real ones as possible and what are the optimal weight for those factors.

**Quick note: on practical application of neural networks.**

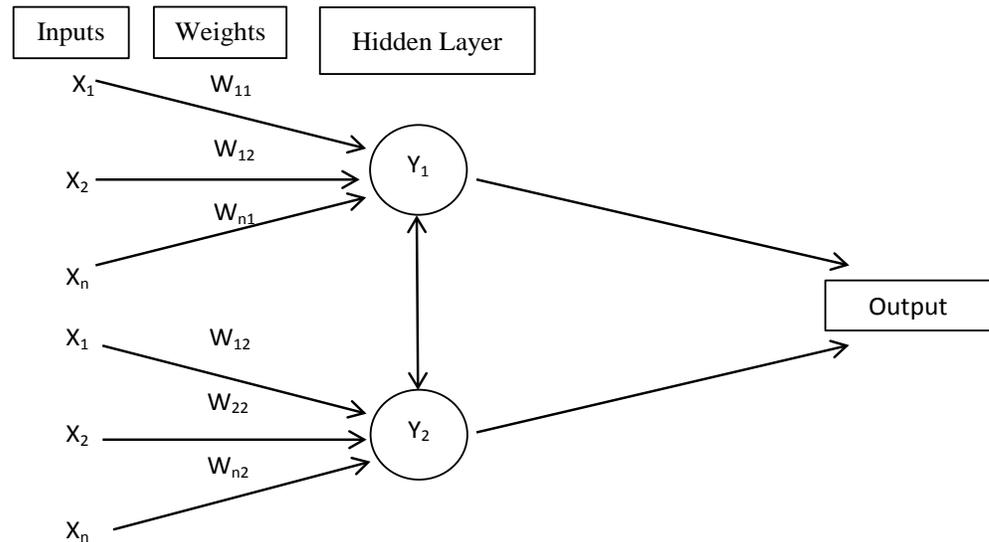
*Studies performed by Elmer and Borowsky (1988) on comparison of bankruptcy prediction abilities of expert systems over credit scoring models showedn that the first ones had 60% accuracy 7 to 18 month before bankruptcy, whereas the credit scoring models prediction rate was 48 per cent at highest (Saunders & Allen 2002).*

### **2.1.2 Artificial neural networks**

Some of the modern literature on the topic (see Allen, 2009) considers artificial neural networks to be part of expert system models. In this Master thesis we follow conservative approach and distinguish these two models. However, we admit that the core of artificial neural networks methodology to a certain extent relates to expert systems methodology, mentioned above.

The very base the idea behind artificial neural networks approach is to estimate expert systems more consistently and objectively using developed software. Structurally, neural network consists of three functional units: inputs, weights and hidden units (a.k.a. hidden layers). Typical two-layer neural system is presented on the Figure 2.1.

Figure 2.1: Neural network



Source: Saunders & Allen (2002)

Its functioning is based on the simulation of the human learning process in a way that the system learns the nature of the relationship between input data and outcome score by repeatedly sampling input/outcome information sets.

In its core neural network accumulates and processes the historical information on repayment experience, financial ratios and default data in order to determine the optimal weights to be given to different factors in various cases. Using predetermined weights, each hidden unit computes the weighted sum of all inputs, and does so until all the input information has been processed. At the final stage information from all hidden units form the output.

One of the major advantages of neural network is the ability to self-evolve – every time neural network estimates the credit risk of a possible loan, it automatically updates its weight scheme (Saunders and Allen, 2002). Another advantage is that given a rather short time horizon (one year) system could predict up to 87% of defaults (Kim and Scott, 1991). Nevertheless, due to its ability to self-educate, neural networks could grow very large in a very short period of time, which result in “overfit” and biased PD estimation.

Another disadvantage of such estimation is the lack of transparency: there is very little or at some cases no economic interpretation given to intermediate steps. This makes it

very hard and at some point almost impossible to check whether the output is consistent. Finally this kind of estimation is expensive to introduce and maintain.

### **2.1.3 Rating systems**

Unlike expert systems, credit ratings are designed to provide independent and objective opinions – not recommendations – on the future state and legal obligation of issuer to make timely payments on their financial commitments (FIB, 2004). Ratings are also quite often used as a reference for the decision making process regarding undertaking the investment decision. Although first ratings had one year time horizon, some of their components, (e.g. credit history data) were available for up to five years.

There are a number of classifications and techniques for credit rating. In this Master thesis we pay special attention to conventional classification, which implicates **external** and **internal ratings**.

External credit rating provided by firms specialized in credit analysis was first offered in the United States of America by Moody's in 1909 (Saunders and Allen, 2002). The solo aim of the company was to provide investors with cheap and accurate information on the financial stability of debt issuers. U.S. Office of the controller of the currency (OCC) was the first governmental institution that developed rating system, which would split the existing loan portfolio of the financial institution into 5 different categories: four low quality ratings (e.g. loss assets, substandard assets, other assets especially mentioned and doubtful assets) and one category for high quality assets.

Later the OCC rating has evolved into six-grade classification scheme, introduced and enforced by National Association of Insurance Commissioners (NAIC) in order to access capital requirements of insurance companies (NAIC, 2008). This rating system was based on the following classification: A and above, BBB, BB, B, below B and default. NAIC ratings were in the great extent consistent with the ratings, performed by insurance companies (ratings coincided in 90% cases (Saunders and Allen, 2002)). This fact has a negative reflection on banks regulatory capital because NAIC rating differed a lot from banks internal rating systems (Carey, 2001). As a result, at the end of 1998 approximately 52% of bank loan portfolios were below investment grading (Treacy and Carey, 2000).

Such inconsistency with NAIC ratings and willingness to meet Bank of

International Settlements (BIS) New Capital accord requirements regarding regulatory capital fostered banks to develop internal rating systems. The architecture of such systems can be one-dimensional, in which an overall rating is assigned to each loan based on the probability of default (PD), or two-dimensional, in which each borrower's PD is assessed separately from the loss severity of the individual loan (the loss given default, LGD) (Saunders and Allen, 2002). In both cases the probability of default strongly depends on how the default events are predicted and on individual bank's risk-rating philosophies (BIS Working paper No. 14, 2005).

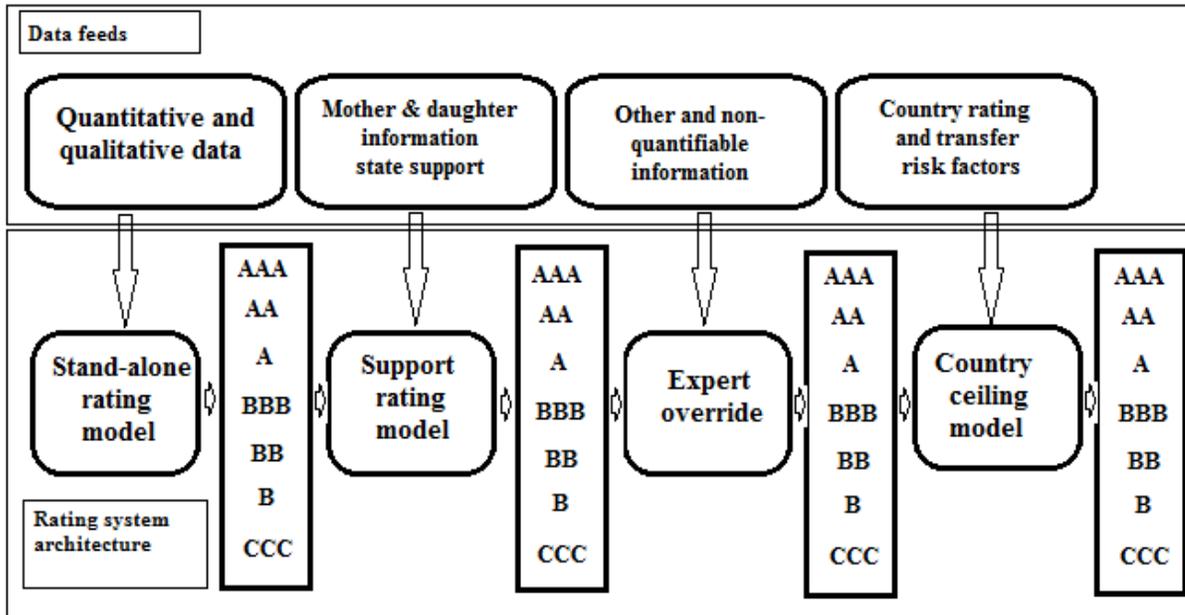
In addition to the two architectures mentioned above, BIS also distinguishes exposure at default (EAD) and maturity approaches as possible bases for rating systems. The EAD, along with LGD and PD is used to calculate the credit risk of financial institutions and expresses a total value of the bank's exposure in case of default. EAD could be estimated either using standard supervisory rules (set by the regulatory authority), or following the advanced methodology, where bank itself determines the appropriate EAD to be applied to each exposure. In this case EAD is calculated based on the robust data and analysis which is capable of being validated both internally and by supervisors (BIS, 2001). Finally, maturity in this case is also treated as a risk component.

Internal ratings became so popular that according to some courses (see Falid, 1999), by the end of 1999 approximately 60 per cent of U.S. banks had various internal rating systems at their disposal, which would cover 96 per cent of large and middle market loans. Notwithstanding most of the banks use similar rating systems, there were certain differences regarding the importance of each of financial risk factors and weights of the given factors. There were also certain differences as to place of qualitative parameters in the rating process.

Typical example of the internal rating system is presented on the Figure 2.2. As it can be seen from the figure below, internal rating system is in a great extent a black box with a lot of information being tight to particular bank practices.

Despite the fact that rating systems, both external and internal, became so popular among banks and regulatory authorities, there are various critiques regarding their underlying methodologies.

Figure 2.2: Example of internal credit rating system



Source: Van Gestel and Baesens 2009

There is also a common belief that one of the causes of 2007-2010 financial turmoil is the failure of ratings agencies and their methods of appropriate estimation of credit risk exposure.

Some of the potential issues with rating systems are as following (Demyanyk, 2008):

- **Circularity** – if a rating agency drops the company rating to BBB (although the previous rating was higher), this would cause an increase in interest rates on bonds, issued by the downgraded company, which would result in higher interest payments. The burden of extra interest payments may cause further problems to issuer, leading to a further downgrade. As a result, company could end up at default.
- **Global inconsistency** – due to the fact that rating business is international with the leading companies having their offices all around the Globe, it is hard to achieve consistency in ratings. The reason for that is different countries follow different regulatory and reporting environments.
- **Anticipation of default** – rating agencies usually react to events rather than predict them, making ratings biased and inconsistent (example: current crisis).
  - **Rating agency power** – decisions made by the rating agencies can have a

large impact on bond's market, e.g. downgrading a bond below investment grade can accelerate selling on such an asset by a number of investors who are not permitted to hold speculative grade debt (Demyanyk, 2008).

- **Limited time horizon** – rating, both internal and external, are only adequate for a certain period of time after which they become biased and inconsistent.

#### **2.1.4 Credit scoring models**

Credit scoring is usually a computer-based system, used by major financial institutions throughout the developed economies in order to measure the creditworthiness of individuals or businesses, set credit limits, manage existing accounts. Banks increasingly implement scoring models to assess credit risk and to calculate how likely it is that borrowers eventually will become delinquent or default (Blochlinger and Leippold, 2005). The objective of credit scoring is to help credit providers quantify and manage financial risk involved in providing credit so that they can make lending decisions quickly and more objectively (Goh Chwee, 2004).

Initially credit scoring was used to estimate credit worthiness in consumer lending. However with increase of the share of medium sized loans in bank's loan portfolios, credit scoring became more popular. Since the individual exposure of such loans is often relatively small, it is uneconomical to devote extensive resources to the credit analysis. Therefore, in case of mid-sized borrowers, banks use credit scoring models instead of rating models (Blochlinger and Leippold, 2005). Nowadays there are number of credit scoring agencies, which have different approaches and models, used in their scoring process.

The methodology of constructing credit scoring models is generally rather simple and involves several steps. Firstly, determination of the scoring range: existing customers are selected and categorized as "Good" or "Bad" based on their credit history and repayment behavior over the given period. On the next step, relevant information on selected customers is collected from loan applications, credit records, and credit bureau's reports. Finally, using waste statistical techniques, credit score is determined.

As for the statistical and qualitative analysis techniques, contemporary literature distinguishes four different methodological forms of multivariate credit scoring models (Saunders and Allen, 2002):

- The linear probability model;
- The logit model;
- The probit model;
- The multiple discriminant analysis model.

The essence of these methodologies lies in identifying financial variables that have statistical explanatory power in differentiating defaulting firms from non-defaulting firms (FIB working party, 2004). At this point are not getting into deeper details of all the methodologies. We concentrate on the fourth, multiple discriminant analysis model and Altman Z-score as a core of it.

The Altman Z-score involves deriving the linear combination of multiple independent variables that will discriminate best between priori defined groups (Hair et al., 1990). Although the idea underlying construction of the model is quite old, it had been modified over time in various ways to avoid biasness and inconsistency and to suite specific industrial needs. The general formula for calculation Altman Z-score is presented below,

$$Z = W_1X_1 + W_2X_2 + \dots + W_nX_n \quad (1)$$

where:

$Z$  is the discriminant score;

$W_1, W_2, \dots, W_n$  are the discriminant weights;

$X_1, X_2, \dots, X_5$  are the remaining ration set that represent the actual conditions of the firm.

Based on the study performed by Allen (2002) which was based on a matched sample of failed and solvent firms, and using linear discriminant analysis, the best fitting scoring model for commercial loans took the following form:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (2)$$

with variables:

$Z$  - cumulative Z-score;

$X_1$  - working capital/total assets ratio (percentage);

$X_2$  - retained earnings/total assets ratio(percentage);

$X_3$  - earnings before interest and taxes/total assets ratio(percentage);

$X_4$  - market value of equity/book value of total liabilities ratio(percentage);

$X_5$  - sales/total assets ratio (percentage).

Most studies revealed that financial ratios measuring profitability, leverage and liquidity had the most statistical power in differentiating defaulted from non-defaulted firms (Saunders and Allen, 2002).

After calculating critical value of the given loan, the outcome is being scaled and classified as “Good” or “Bad” taking into consideration the cut-off point. The relevant cut-off point could be determined and adjusted with respect to exogenous economic conditions, industry specifics etc. Companies with Z-score more than **3** are considered creditworthy and financially stable. Z-score values between **1.81** and **2.99** determine the so-called “grey area” – firms which fall in within this range are considered uncertain as to the credit risk exposure. Entities with Z-score below **1.81** are considered to be close to default or even failed.

Although scoring models are relatively inexpensive to implement and do not suffer from the subjectivity and inconsistency of the expert systems, there are still a few questions that need to be mentioned.

One of the major limitations of scoring models is data availability. Although data which are used for this type of analysis are updated monthly, in most of the cases it only has one source – financial statements. As such, they heavily depend on internal accounting standards and not that much on market valuation. Another shortcoming is that Altman Z-score model is based on the linear dependence between variables, whereas the path to bankruptcy in some cases is highly non-linear, which implies that the relationship between X's is most likely not to be linear either (Saunders and Allen, 2002, Kim 2007).

The above mentioned drawbacks could cause two types of outcomes (errors):

- Type one error – lending to a bad customer;
- Type two error – denying the good customer.

Moreover, economic theory itself gives very little guidance as to why a particular

ratio could be useful in forecasting defaults. All of the mentioned issues were addressed and partially solved using structural credit risk measurement models.

## **2.2 Further evolution of traditional risk management approaches**

*“While in many cases multivariate accounting based traditional models have been shown to perform quite well over many different time periods and across many different countries, they have been subject to a number of critiques” (Altman and Saunders 1998, pp. 1722):*

- Their reliance on book value accounting data, which is rather inflexible and periodical;
- Traditional models assume a linear dependence between explanatory variables, whereas the real economic conditions have proven to be non-linear;
- Third, the credit-scoring bankruptcy prediction models, described in Section 2.1.4, are often only tenuously linked to an underlying theoretical model.

*“As such, there have been a number of new approaches - most of an exploratory nature, that have been proposed as alternatives to traditional credit-scoring and bankruptcy prediction models” (Altman and Saunders 1998, pp. 1724).*

### **2.2.1 Structural Models of Credit Risk Measurement**

Structural models estimate PD through valuation of not only assets but the whole balance sheet data, i.e. the structure of the company. Therefore structural models provide a link between the creditworthiness of a borrower and its economic and financial conditions. In this case PD is endogenously generated within the model instead of being exogenously given e.g. in reduced form approach (Abel, 2005).

One of the most distinct structural models started by introducing option pricing theory by Black-Sholes (1973) and Merton (1973). Building on it, Robert C. Merton in 1974 (Bharath and Shumway 2004) developed the model, which was later reinterpreted by KMV Corporation (further referred as KMV-Merton model). Since then the model has become extensively used worldwide. KMV-Merton’s model is based on two crucial assumptions (Bharath and Shumway, 2004):

- Total value of the firm follows geometric Browning motion;
- Firm has only one discount bond outstanding.

Taking into account these assumptions, model treats equity of the levered firm as a call option on the firm's assets with a strike price equal to the debt repayment amount. In this case, at maturity, firm's shareholders can exercise the option to purchase company's assets in case market value of assets is higher than its debt value or face the default otherwise. It means that probability of default until expiration is equal to the chance that the option will expire out of the money (Saunders and Allen, 2002).

In case of KMV – Merton model, market value of the firm is a sum of the market value of the firm's debt and market value of the firm's equity. Although it is relatively easy to determine the market value of the firm's equity from the stock market, it gets slightly complicated with determination of market value of the firm's debt in case it is not publicly traded. Based on this market value of equity could determine using Black-Scholes formula (Eq. 3), and value of the firm's debt equals value of a risk-free discount bond minus the value of a put option on the firm, with a strike price equals to the face value of debt and maturity a time T (15).

$$E = VN(d_1) - e^{-rT}FN(d_2) \quad (3)$$

where:

$E$  – market value of the equity (real number);

$F$  – face value of the firm's debt (real number);

$R$  – risk free rate (percentage);

$N(.)$  – cumulative standard normal distribution function;

$$d_1 = \frac{\ln(V/F) + (r + 0.5\sigma_v^2)T}{\sigma_v\sqrt{T}} \quad (4)$$

$$d_2 = d_1 - \sigma_v\sqrt{T} \quad (5)$$

Taking into account Black-Scholes formula and critical assumptions mentioned above, the volatility of the firm and its equity is determined by Eq.6 ( $d_1$  – is determined in the Eq. 4). Estimation of volatility of the firm's equity is based on historical stock returns

information or option volatility data (Bharath and Shumway, 2004).

$$\sigma_E = \left(\frac{V}{E}\right) N(d_1) \sigma_V \quad (6)$$

Determination of probability of default in KMV – Merton model is based on simultaneously solving the equations (2) and (3) for  $V$  and  $\sigma_V$ . Once these values are obtained probability of default could be ( $\pi_{KMV}$ ) determined by Eq. 7.

$$\pi_{KMV} = N \left[ - \left( \frac{\ln(V/F) + (r + 0.5\sigma_V^2)T}{\sigma_V \sqrt{T}} \right) \right] = N(-DD) \quad (7)$$

The main advantage of the KMV-Merton model is determination of the expected probability of default through option pricing model, which implies volatility of equity values. Market value of the equity almost immediately evaluates and reflects any changes in the company's structure or any other event, which is known to the public. This makes this model more efficient than external credit ratings. Example of importance of such sensitivity is presented below.

**Quick note: on sensitivity issues – case of Enron**

*Bankruptcy of Enron Corporation is considered to be one of classical examples of credit rating failures. Being one of the leading energy companies on the territory of United States of America, Enron went bankrupt in 2001 due to institutionalized, systematic and creatively planned accounting fraud. Before its crash, Enron's stock prices began to fall and it took rating agencies couple of days to downgrade its outstanding debt securities to a lower investment level. This time delay between actual event and downgrade caused huge losses for investors.*

**2.2.2 Reduced form Model (risk neutral valuation approach)**

Unlike structural model, paying special attention to company's asset-liability structure, reduced form models focus solely on the firm's traded liabilities (bonds) and default-free term structure (Wi.-Ing and Bernhard, 2008). In this case default probabilities

are taken either from the observable values of traded securities or estimated from historical data of defaults and relevant explanatory variables.

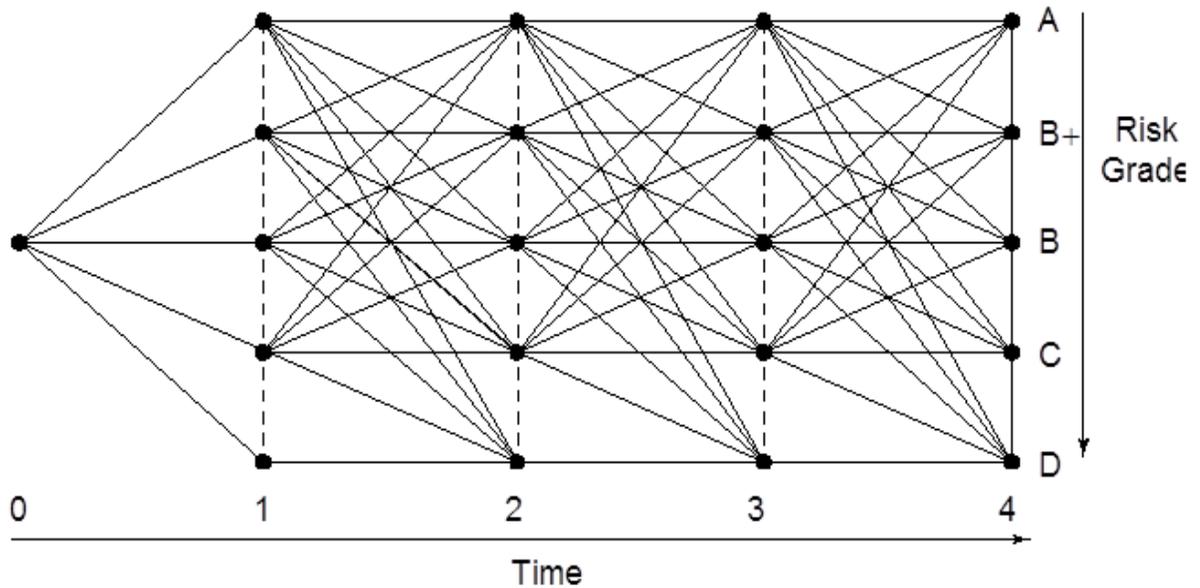
The framework, reduced form models operate in, is a risk neutral market, where all investors are assumed to accept the same expected return as that, promised by the risk-free asset. Taking into account such behavior, the assets price could be determined by discounting expected future cash flows on an asset by the risk free rate (Gallati, 2003). Risk-free rate of return could be applied to get the forward looking risk neutral probability of default. One of the major issues with using a risk neutral probability of default in measuring exposure to credit risk is a very short time horizon: derived estimates of PD are only consistent for 1 year period.

One of the attempts to extend the time horizon of valuation was undertaken in KPMG, approach which became popular and widely used in financial institutions all over the globe as an instrument for both default prediction and loan valuation.

It is based on decomposition of the yields into credit risk free rate and credit risk premium. The credit spread is then calculated based on the estimated probability of default multiplied by loss given default.

A specific application of KPMG's methodology is a KPMG loan analysis system. It is based on the objective assessment of probability of default of a loan or a bond using net present value approach (NPV) to credit risk valuation (Saunders and Allen, 2002). Using a "multinomial tree" analysis, commonly used in bond valuation, KPMG model estimates the influence of opposite in its influence events, (e.g. internal and external events, which could lead to revaluation of the loan) which could influence the bond price, and assess its value in all possible cases (upgrades or downgrades). By doing so model is trying to estimate (predict) the possible value of the loan (portfolio) in the future, taking in consideration both the best case and the worst case scenarios. Example of a "Multinomial tree" is given on the Figure 2.3 below.

Figure 2.3: Credit migration graph for loan with a four year time horizon



Source: Saunders and Allen, 2002

Figure 2.3 is a simplified illustration of possible credit rating movements of a B rated borrower over a four year time horizon. The originally B-rated borrower, given the transition probabilities, could move towards a higher or lower grade, or even end up in default. While these migrations are taking place, banks develop the system of spread reprising for different quality borrowers, as a mechanism of credit risk mitigation.

Based on number of studies (see Bharath and Shumway, (2008); Campbell et al (2008), and Jarrow, Mesler and van Deventer (2004)), main advantage of the structural models (and KMV-Merton model in particular) is assumption that company's liability structure is stable over time. This means that even though market value of corporate assets is volatile, its debt structure is constant overtime (Bharath and Shumway, 2008). KMV-Merton model also allows making forward-looking prediction of default probability, unlike history-based prediction methods (Gallati, 2003).

However, KMV-Merton model is often being criticized for using prices, taken from the corporate debt markets, which are less liquid then the equity markets. Model also considers two credit states: default and non-default, without recognizing several rating buckets.

## **2.3 Modern approaches for measuring credit risk**

Before proceeding with analysis of modern approaches for credit risk measurement, it is important to mention that almost all of them were developed as an extension of methodologies and techniques mentioned in the previous chapter. Modern approach to credit risk measurement became more sophisticated and involve a substantial number of calculations, which made them more profound and less vulnerable.

### **2.3.1 Credit Metrics and other VaR approaches.**

Before we introduce the formal idea of Credit Metrics, it is useful to briefly describe the main idea of the Value at Risk approach to measuring credit risk.

Value at risk (VaR) was developed as a risk measuring tool by practitioners in mid-90<sup>th</sup>. One of its undoubtfull advantages is the ability to measure the value of a capital at risk under extreme conditions in trading portfolios that could be updated on the regular bases (Damodar, 2008).

In general form, value at risk estimates the maximum loss of value on a given traded asset (portfolio) or liability over a given time period at a given confidential interval (Gallati, 2003). Confidence level in this case determines the reliability of estimation and could be 95, 97.5, 99 per cent. This implies that the loss higher than value at risk could be suffered only with very small probability. Based on assumptions used in its calculation, VaR incorporates credit risk of a portfolio into one single number, convenient to use and understandable (Linsmeier and Pearson, 1996).

#### **2.3.1.1 Basic approaches to VaR measurement**

There are three basic approaches commonly utilized for estimating Value at Risk. It can be determined by **comparing portfolio with a historical data, using Monte Carlo simulation** or analytically **using variance covariance across risk**. These approaches differ in data they use and degree of precision. That is why they require closer look.

Historical simulation is considered to be the easiest way to estimate VaR. It requires rather small number of simplified assumptions regarding statistical features of market factors (a.k.a. market rates). Historical approach creates hypothetical time series of returns on a portfolio by processing given portfolio through real historical data and computing

changes that would occur in each period.

The first step in estimation of VaR using historical simulation contains determination of market factors by breaking (mapping) the instruments in the portfolio to the simpler, more standardized instruments, more explicitly connected to original risk factor (e.g. a six-year coupon bond with annual coupon  $K$  could be broken into 6 zero coupon bonds) and obtaining the mark-to-market value of the asset in terms of market factors (Linsmeier and Pearson, 1996). In a second step we gather historical data on the given market factors for a predetermined period of time and process the given hypothetical market factors through real historical data (Damodar, 2008). Afterwards we compute changes that would occur in each period (profits and losses which could occur with certain determined recurrence).

Finally we arrange the mark-to-market profits and losses, obtained in the previous step from the bigger profit to bigger loss and determine asset's (portfolio) VaR using predefined probability (Linsmeier and Pearson, 1996). Brief example of VaR estimation using historical simulation is given in the quick note at the end of this subsection (From Cabedo and Moyan, 2003).

Advantages of historical simulation approach are the following:

- Historical simulations provide results, easily understandable and communicable among both mid-level practitioners and top management because their logic is quite simple and straight forward;
- There is no need for any assumptions regarding functional form of market factor's return distribution. The only supposition in this case is a historical distribution of the future returns;
- Historical simulations captures correlation structure reflected in market rates changes, and assumes it to be constant overtime, which makes it technically easy to implement the approach (in case of a single instrument portfolio) (Sironi and Resti, 2007).
- VaR estimated using historical simulations, is insensitive to dynamic market conditions (consider a high confidence level e.g. 95, 99 percent).

However, there are certain limitations of historical simulations:

- In case of a large portfolio, consisting of complex financial instruments, historical simulations become time consuming and technically complicated (Sironi and Resti, 2007).
- Assumption that future distribution of market factor changes would follow historical pattern is rather doubtful and only consistent in the long run.
- Although all three approaches to VaR estimation rely on historical data, in case of historical simulation, this is the only source of information used (Damodar, 2008). This leaves very little if any space for alternative assumptions regarding risks distribution (which makes it a non-parametric approach) or introduction of subjective judgments regarding the distributions functions.
- Historical simulation implies data points are weighted equally, which is quite a fragile assumption in economic realities. Plus it is quite obvious that in certain cases historical market data might not be available, which makes it impossible to perform historical simulation to estimate VaR.

Some of the limitations were addressed by introducing variance/covariance approach for VaR estimation. It is based on the assumption of Normal distribution of market factor returns (unlike historical simulation approach).

Variance/covariance approach is the estimation of the volatility of an asset (portfolio) returns and correlation between the asset price movements. Although this technique is more often used for valuing market risks, its contribution to credit risk estimation is impossible to overestimate. That is why we present a simplified analysis of this technique below.

VaR calculating using variance/covariance matrixes at some point has very much in common with historical simulation. We firstly use the same mapping procedure as we did in the first step for historical estimation, only assuming that changes in market factors follow Normal distribution with mean of zero we estimate their variability and co-movements (Gallati, 2003). In the second step each financial asset is stated as a set of positions in the standardized market instruments (Damodar, 2008). In the third step using products of the standard deviations of the market factors and the sensitivity of the standardized position to changes in the market factors we determine the standard deviation

of these changes (based on historical information). Finally, having weights on the standardized instruments, variance and covariance in these instruments we can determine the portfolio's variance and standard deviation using statistical formulas.

Although, variance/covariance approach is a lot more sophisticated and simple to perform, having made all the necessary assumptions in place and inputted required data, it runs to following limitations:

- The assumption of Normal distribution of the market returns is doubtful considering empirical studies which indicate, that the return's distribution in this case has slightly different features: their tail are fatter (Gallati, 2003). This could cause the undervaluation of a true VaR by the computed VaR;
- Assumption of linear correlation between market factors and changes in the market value of a portfolio also make the variance/covariance approach quite fragile due to its incompatibility with behavior of certain financial instruments (e.g. bonds, the market value of which changes significantly with the change in maturity) (Sironi and Resti, 2007);
- The estimates might be imprecise because if the variance/covariance matrix is incorrect.

The Monte Carlo simulation as a risk assessment tool pays special attention not to entire distribution of the market returns (as variance/covariance estimation does), but to the probability of default (or loss), which goes beyond the given value.

Peculiarity of the Monte Carlo simulation is that, although VaR estimation follows the same first and second steps as variance/covariance simulation, third step is quite different. Unlike historical simulations and variance/covariance approach, where market factors follow already determined distribution, in case of Monte Carlo simulation we have opportunity to choose the distribution function. In addition it is possible to bring in subjective judgments to modify these distributions (Damodar, 2008). Once the distribution function is chosen, the random generator is used to deliver the number of hypothetical values of changes in market factors. The bigger the number of iterations, the closer the estimated VaR gets to the real one. Hypothetical profits and losses of a portfolio are then calculated by subtracting the actual mark-to-market portfolio values from the hypothetical portfolio values (Hypothetical portfolio values are calculated using market factors, obtained

in the previous step). Finally we range results, obtained in the previous step from the bigger gain to the bigger loss and given the loss probability we get the VaR estimation.

Although Monte Carlo simulation is often thought to be more sophisticated approach than others (various distribution assumptions could be made, covers any type of portfolio), mentioned in this part of the Master thesis, with the increase of number of risk factors these simulations become technically difficult to implement – hundreds of thousands of simulations has to be performed to obtain a reliable result.

As a general remark to all the basic approaches for VaR measurement, overviewed above, we would like to mention that, given the identical assumptions, they all yield roughly the same VaR estimates. As it was also mentioned above, the first two approaches are based on market data, which at some cases (e.g. not publicly traded securities or lack of information) might be serious issues for performing necessary calculation. As a solution for this shortcoming, J.P. Morgan (together with Bank of America, KMV and others) developed Credit metrics, a unique framework for VaR calculation, main features of which are described below.

### ***2.3.1.2 Credit Metrics innovations***

The necessity to develop Credit Metrics as a framework for VaR calculation was quite obvious, as there were no way to estimate risk of non-publicly traded assets (e.g. loans and bonds). Credit Metrics is also considered to be a modification of the KMV-Merton model in a way that it determines the default probability of a given security (or portfolio) using rating classes (Lutkebohmert, 2008). One of the most important assumptions of the model is that all variables, except current rating state of the issuer, are fully predictable over time. This implies that value of a security mainly depends on the rating of the issuer at a given point of time (Trueck and Todorov, 2009)

As it was noted before, in case of non-traded securities we are short of both market price and volatility information for performing VaR estimation. However, using available data on a borrower's credit rating, migration probability, recovery rates of default loans, credit spreads and yields on the relevant market we could estimate market value on non-traded security, and thus VaR (Saunders and Allen, 2010). Given that issuer is not in a state of default at the risk time horizon, the value of the bond or a loan determined by

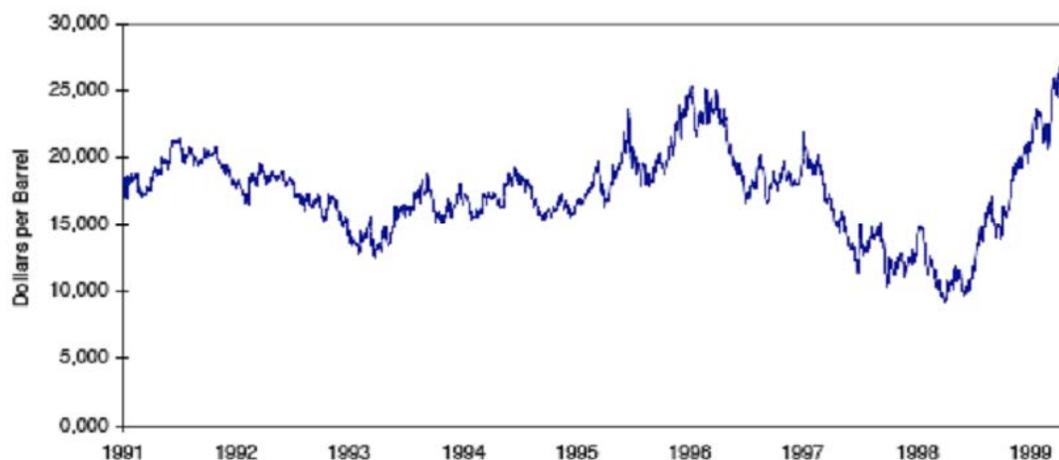
discounting outstanding cash flows using relevant credit spreads over the riskless interest rate.

As a risk management tool this model is applicable to all kinds of financial instruments with intrinsic credit risk, which is undisputed advantage (Trueck and Todorov, 2009). On the other hand default and migration probabilities consider to be constant within the rating classes, whereas in KMV-Merton model they are calculated internally. Although Credit metrics model allow estimation of VaR for non-traded assets, the assumptions, it is based on (particularly heavy dependence on the rating) decrease the level of reliability of VaR estimates.

**Quick note: on price sensitivity importance.**

*Using daily data on Brent Crude Oil Prices from 1992 to 1998 Cabedo and Moya simulated historical approach for VaR estimation. Data is presented on the figure below.*

**Figure: Price/barrel for Brent Crude oil over the period 1992-1999**



Source: Cabedo and Moya, 2003

*After separating daily price changes into positive and negative, they've defined the positive VaR as the price change in the 99<sup>th</sup> percentile of the positive price changes and the negative VaR as the price change at the 99<sup>th</sup> percentile of the negative price change. After performing calculation they've concluded that the daily Value at Risk at the 99<sup>th</sup> percentile was about 1% in both directions (Damodar, 2008).*

### 2.3.2 The Macro Simulations Approach

One of the major drawbacks of credit metrics framework is an assumption of rating migration probabilities being constant across rating classes and business cycles. However studies of Hol (2001), and Burn and Redwood (2003) showed that macroeconomic conditions can significantly influence the probability of downgrade or default on a security or portfolio. Hence not only internal factors but also external factors, e.g. the characteristics of the industry an issuer belongs to, state of the economic cycle, can influence bankruptcy rate and consequently VaR estimation.

Introduction of external shocks influencing default process of estimation cause VaR estimation to be rather inconsistent and biased at the state it was overviewed earlier. Thus the necessity to account for macro factors was quite crucial for sound credit risk policies in banks.

Saunders and Allen (2002) propose two ways to deal with cyclical effects:

- Simulate the evolution of migration probabilities for the whole time period taking into account development of macroeconomic factors (CPV-Macro);
- Divide historical data on recession and non-recession periods and yield two different VaR estimations (CPV-Direct).

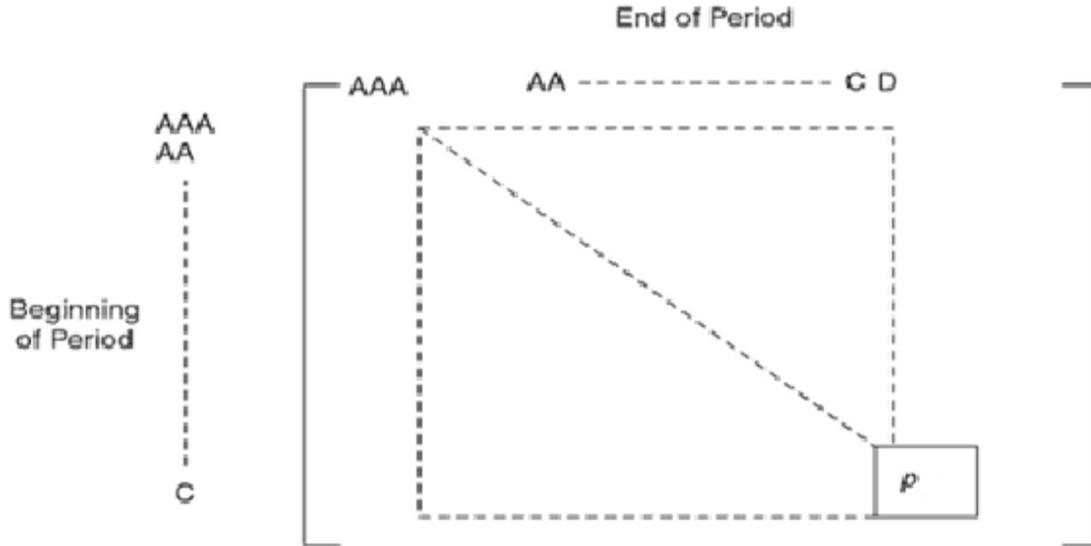
Although Macroeconomic simulation (a.k.a. CPV-Macro) uses the same transition matrix as Credit Metrics, let us first overview the whole process of CPV-Macro estimation in more detail.

Critical assumption in CPV-Macro is that credit migration probabilities show random fluctuations. Possible explanation for such a behavior is a volatility of economic cycles. Model also assumes that different risk segments, onto which borrowers are classified, react in a different way to various economic fluctuations. Assuming that non-systemic risk has been minimized (diversified) for the total number of borrowers, it has to be systemic risk, which is responsible for joint default correlations, thus have to be considered.

Figure 2.4 formalizes the transition matrix for a hypothetical country, where each cell represents the probability that a particular counterparty, which was already given a rating, will move to another rating by the end of the period. This approach assumes that

each probability of rating transition (e.g.,  $P$ ) is a constant parameter (Saunders and Allen, 2002).

**Figure 2.5: Historical (conditional) transition matrix**



Source: Saunders and Allen, 2002

Keeping in mind that all probabilities in each row of the transition matrix must sum up to one (an increase in one probability must be compensated by decrease in other probabilities), Model assumes that  $P$  vary together with macroeconomic conditions and random shocks. In general terms the equation would be the following:

$$P = f(X_{it-j}; V_t, \varepsilon_{it}) \quad (8)$$

Given that:  $i = 1, \dots, n$  and  $\varepsilon_{it} \sim N(0, \sigma_\varepsilon^2)$

where:

$P$  - probability of rating transition (real number);

$X_{it-j}$  - lagged macroeconomic variables, determined by historic information (real number);

$V_t$  - general economic shocks (real number);

$\varepsilon_{it}$  - random shocks for each of the macro variables (real number).

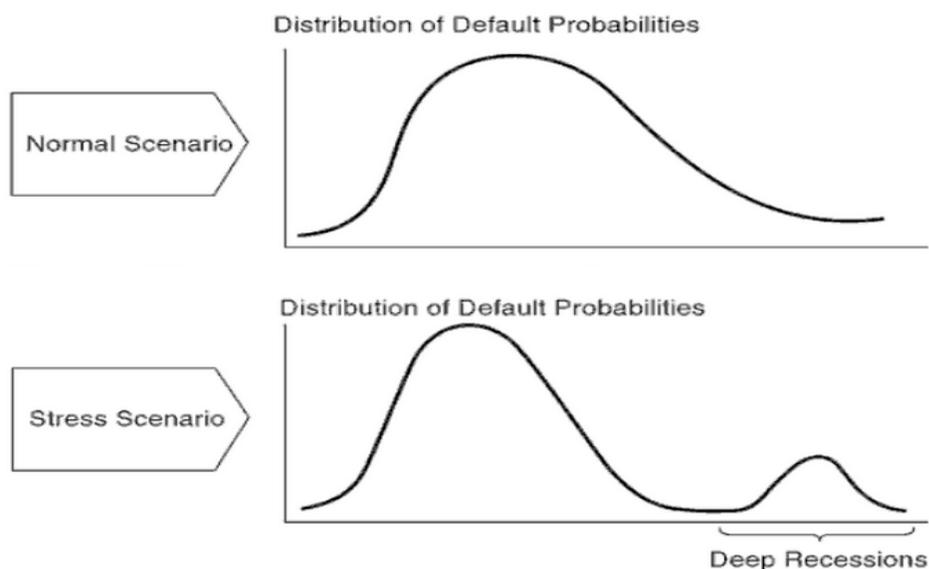
Because macroeconomic variables are historically defined, all we need to do is to calculate future development of general economic shocks and individual macro shocks using Monte Carlo simulation approach (Saunders and Allen, 2002). The results on this simulation together with macroeconomic variables are used to estimate the value of transition probability into the future, which afterwards is used to determine VaR. There is rather large number of variables, which are considered to be significant in predicting bankruptcy under different circumstances. Most commonly used data are GDP, monetary aggregates, unemployment and stock indices (Lutkebohmert, 2008).

One of the shortcomings of CPV-Macro is that it explicitly uses forecasted values of macro variables without making any assumptions about the distribution of probabilities of default. This issue was taken into consideration while developing alternative version for credit portfolio view, named CPV-Direct.

Predetermination of default's distribution as well as correlations among industry risk segments is the essence of CPV-Direct model (Saunders and Allen, 2002). Therefore model uses historic probabilities of default in order to estimate both the shape of distribution and correlation of probabilities of default across industry. Finally migration probabilities are determined depending on the risk factor for each segment (Lutkebohmert, 2008). Vulnerability of business cycle condition is introduced in the model by means of changing assumptions regarding the distributions.

Figure 2.4 illustrates introduction of negative expectations and their effect on default probability distribution. The upswing in the tail reflects the assumption that, with the worsening economic conditions, high risk borrowers are more likely to go bankrupt (decrease the rating level).

Figure 2.6: Stress test for CPV-Direct



Source: Saunders and Allen, 2002

The only major shortcoming of the CPV-Direct model is its requirement of a large number of data to be used in order to yield consistent results, which is not always possible in case of certain securities.

As a summary for the macroeconomic simulation approaches for credit risk estimation it is worth mentioning that both CPV-Macro and CPV-Direct should be viewed as complementary to Credit Metrics since they account for the drawbacks (e.g. overtime static transition probabilities).

### 2.3.3 The Insurance Approach

Before going into deeper detail of insurance approach for credit risk measurement it is worth mentioning that insurance ideas in this field are quite new and there has been very little if any literature on this topic.

In its core, insurance approach includes model, which was developed and introduced as credit risk measurement and management tool and was named the mortality analysis.

Mortality analysis approach to credit risk measurement is based on usage of portfolio of loans or bonds and their historic default data to produce a table that can be used in a predictive sense for one-year, or marginal mortality rates ( $MMR_i$ ) and for

cumulative mortality rates (*CMR*) (2). Technical table calculation is quite straightforward. Using formula below:

$$MMR_i = \frac{\text{Total value of } B \text{ graded loans defaulted for period } i}{\text{Total value of } B \text{ graded loans granted for period } i} \quad (9)$$

Using formula one calculate individual  $MMR_i$ , and afterwards, based on the data from the whole sample, determine weighted average  $MMR_i$ , which is later inserted in the mortality table. Weight in this case should be adjusted to reflect the relative issue size in different years. Thus the average  $MMR_i$  in year  $i$  would be determined using following equation:

$$MMR_i = \sum_{i=1}^n MMR_i \cdot \omega_i \quad (10)$$

where:

$MMR_i$  - marginal mortality rate (percentage);

$\omega_i$  - weights for the mortality rates (points).

But what is more practically useful is calculation of cumulative mortality rate (*CMR*), which determines probability of default of the loan/client over a period longer than 1 year. Calculation is based on determination of survival rate (*SR*) which is determined as percentage of loans or bonds of a given grade, which did not go default (opposite to mortality rate). Formula for calculation of the survival rate is presented below:

$$SR_i = 1 - MMR_i \quad (11)$$

where:

$SR_i$  - survival rate of a particular loan/portfolio (percentage);

$MMR_i$  - marginal mortality rate (percentage).

Having defined survival rate, cumulative mortality rate would be equal to:

$$CMR_i = 1 - \prod_{i=1}^n SR_i \quad (12)$$

where:

$CMR_i$  - cumulative mortality rate of a loan/client (percentage);

$SR_i$  - survival rate (percentage).

Example of mortality table, calculations of which presented above, is given in Appendix 2.

As a brief conclusion for this sub-part of this Master thesis we would like to make couple of remarks.

Firstly, we have briefly gone through the evolution of the credit risk measurement models: starting from the very first ones, which were based on the subjective judgment of the individual. Following more sophisticated models, which used technical assets (such as computer software and hardware) for bankruptcy prediction. Finally finishing with modern approaches, which took into consideration incredibly large number of variables for prediction of probability of default.

Secondly, we managed to implicitly compare the existing methodologies. Finally, we determined strengths and weaknesses of both modern and classic risk measurement techniques in order to get a better insight into the credit risk measurement issues.

In the next part of this Master thesis we will perform a practical exercise by computing Altman Z score model for chosen industry in UK. Further, we will to determine if this DP prediction model proved reliable in forecasting actual defaults.

### ***Chapter 3. Practical exercise: Computation of Altman Z-score & estimation of its reliability***

As part of the research question, stated in the introduction part we are interested not only in theoretical aspects of credit risk measurement, but also in practical, in particular how reliable are the most commonly used models in predicting bankruptcies. In the following part of this Master Thesis we examine ability of Altman Z-score to forecast business failure.

The idea of predicting bankruptcies is not new. Multivariate prediction of bankruptcy as established by using univariate analysis of bankruptcy prediction was initially developed by Beaver (1967, 1968) (Gerantonis and Vergos, 2009). He managed to determine a number of indicators based on company's accounting data, which were behaving differently in failed and non-failed companies over a certain period of time before filing for bankruptcy procedure. Later model was redefined and improved by Altman (1968) and was named Altman Z-score.

Although model, developed by Altman, is considered to be a bit simplified and does not account for as much default factors as some of the more advanced techniques, it is still widely used by various institutions due to its relevant transparence and availability.

The most recent examination of the model was made by Grice and Ingram (2001) and Gerantonis and Vergos (2009). Both studies conclude that the model has sufficient prediction ability and could be used by financial analysts and portfolio managers for stock picking and asset management. In this part of the master Thesis we are not only analyzing the ability of Altman model to predict failures but also determine the significance of variables, used for this estimation.

Before getting down to actual data analysis, it is quite important to analyze the development of the major indicators of Great Britain Construction and Material industry as they are at the moment and its development over the past years (including both pre and after crisis data). Comparison of pre-crisis and after-crisis data will give us a great insight to this industry. In the following subsection we go through the major trends in Construction and Material industry in Great Britain, such as the sectorial breakdown, number of companies, registered in each sector, number of people employed and the added value.

### 3.1 Characteristics of construction sector in Great Britain

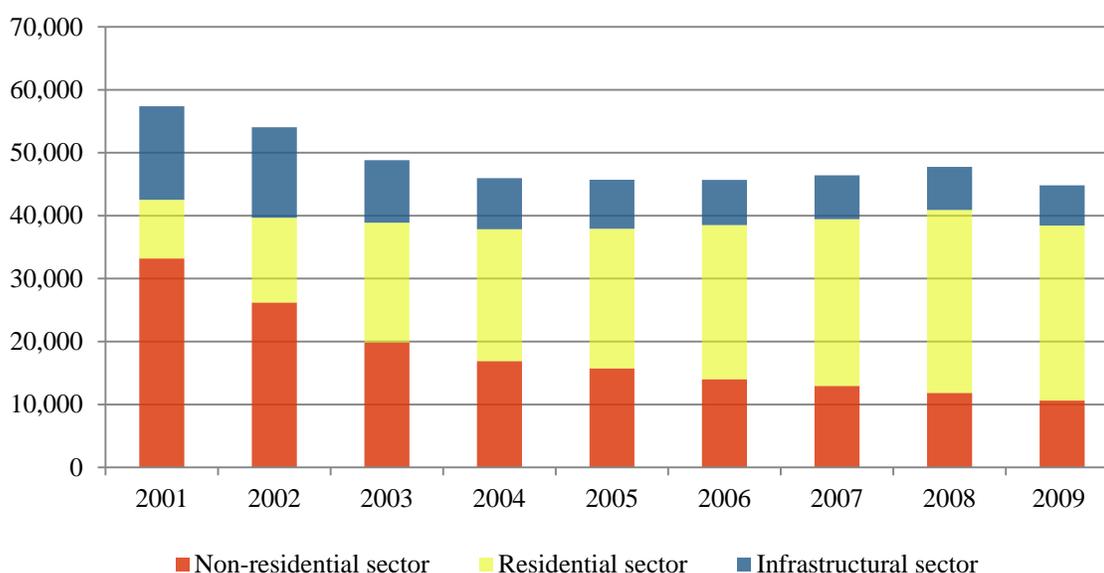
As in most post industrial countries, construction industry in Great Britain is one of the most profound drivers of the GDP. Being such, it has historically shown cyclical patterns in its developments. Such a behavior could be explained by fluctuations in consumer confidence, availability of credit (often in the form of mortgages), political events (such as a construction boom in Germany following reunification) and general economic cycles. The peaks and troughs in development activity tend to be more amplified than those for the whole economy, perhaps as a result of large projects being postponed and/or cancelled during periods when economic output contracts (Stavinska, 2010).

In addition construction sector could be subdivided onto the following subsectors:

- Residential sector – involves construction of housing and residential complexes;
- Non-residential sector – involves both commercial and industrial subsectors of construction industry;
- Infrastructural sector (civil engineering) – usually non-profit construction in such industries as medicine, chemicals, power generation etc.

More detailed industrial breakdown and a brief analysis of the number of companies registered in each subsector is presented on the Figure 3.1

**Figure 3.1: Construction sector sub sectorial breakdown according to the number of companies (for the period 2001-2009)**



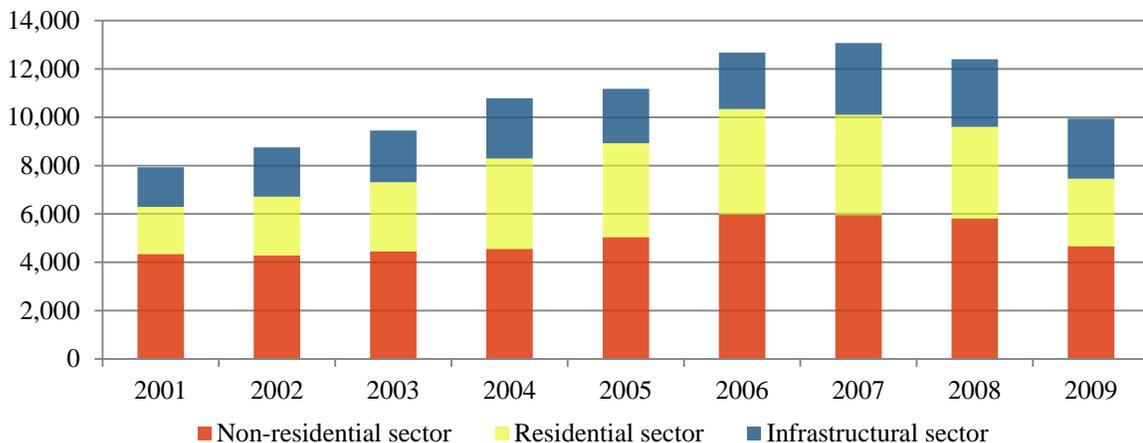
Author's calculations, data from ONS, 2010

Based on the information from the Figure 3.1 we can conclude that the overall number of companies in the construction sector decreased for the period of 2001-2009 by 22 per cent (with the most substantial year to year decrease over the years 2002 and 2003 by 10 and 6 per cent subsequently). This could be explained by increase in level of competition on the market (as a result a number of companies just could not face it and went bankrupted), substantial increase in level of industrial concentration (35 per cent of the total value produced in the sector is produced by top 10 companies (ONS, 2010)). The 2007 Global recession has also played its role in this process.

As to sectorial breakdown, there has been a gradual shift from prevalence of commercial and industrial construction to residential. The figure above shows that despite the overall decrease in total number of companies, the residential sub sector increased from 16 per cent to 62 per cent and industrial sub sector decrease from 58 to 24 per cent with infrastructural sub sector being relatively constant over the period analyzed. Possible reason for such a tendency might be an increase in availability of residential financing, which was followed by increase in demand for residential property and subsequently increase in total number of companies in relevant subsector. On the other hand consolidation of non-residential sector and the following increase in concentration could be the reason for decrease in the number of companies.

As to the total value added by construction sector in total and sub sectorial breakdown, it is presented in the Figure 3.2.

**Figure 3.2: Value of work done by major construction subsectors for the period 2001-2009 (in million £)**



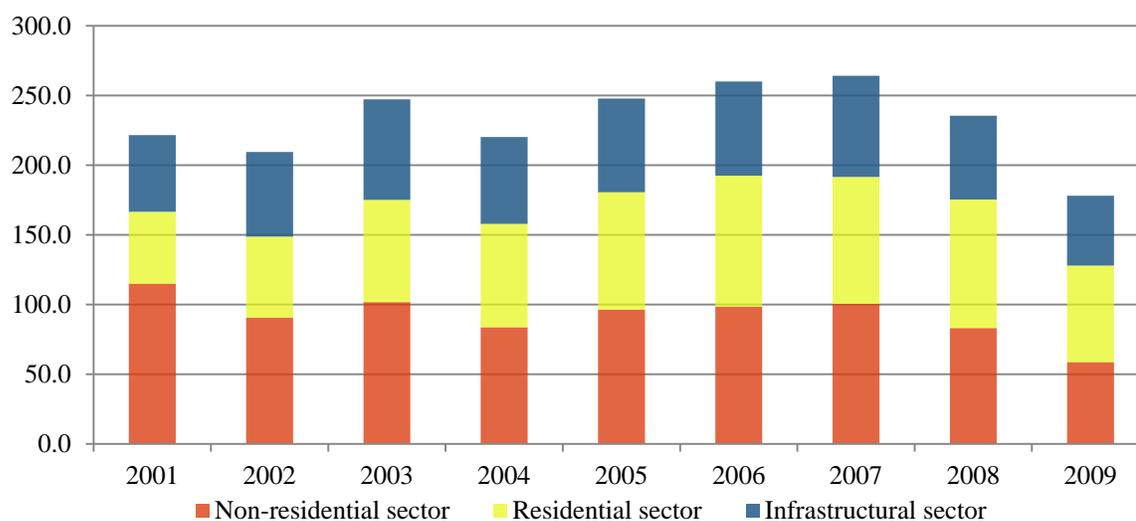
Author's calculations, data from ONS, 2010

From the graph above we can see that there has been a positive tendency in development of construction industry as such for the period 2001 – 2007. Total value added in the industry has increased from 7.9 bln. £ in 2001 to 9.9 bln. £ in 2009 (which makes the average from year to year growth rate to be 3 per cent). The obvious reason for a 36 per cent contraction of added value for the period 2007-2009 is a general economic downturn caused by subprime mortgage crises in United States.

As to sub sectorial breakdown, non-residential sector has been the most productive over the period analyzed with the average share value of total output of 47 per cent (with maximum of 55 per cent (4,3 bln £) in 2001 and minimum of 42 per cent (4.5 bln £) in 2004). As to the share of residential and infrastructural sectors, they've been rather stable over the period of analysis with the average value of 30 and 22 per cent respectively. Although the number of companies in non-residential sector has been decreasing (as seen from the Figure 3.1) its share in the total value has been substantial. Such a phenomenon is caused by increase in the level of industrial concentration, increase in available financing and general economic conditions. Although the overall forecast is quite promising, the general downturn in construction sector is quite obvious.

As to the number of people employed in the industry, the relevant breakdown is presented in the Figure 3.3

**Figure 3.3: Total number of people employed in the construction industry for the period 2001-2009 (including sub sectorial breakdown) (in thouthends)**



Author's calculations, data from ONS, 2010

The overall number of people employed in the industry has been rather volatile for the period analyzed with the maximum of 2.64 million people employed in 2007 (pre-crisis year) and minimum of 1.78 million people employed in 2009. The overall decrease in the number of people employed in the industry for the period of analysis has decrease by more than 20 per cent. Although the overall positive tendency is present until 2007. The following downturn could be explained by sharp decrease in demand for both residential and non-residential sectors, caused by World recession.

**Brief note: development of construction industry in EU**

*If we'll look down on the development of construction industry in EU 27, it would be quite amazing how the tendencies it the construction sector in UK would be similar to the ones of EU.*

*Construction activities in the EU -27 provided employment to an estimated 14.8 million persons in 2007 (which was almost 11.5 per cent of non-financial business economy workforce). Total value added, generated by the industry totaled to EUR 562 billion (9.3 per cent of the non-financial business economy's total value added) (Stawinska, 2010)*

As to the sectorial breakdown, non-residential sub sector has been the biggest employer in the industry with the average 40 per cent share (with maximum of 52 per cent in 2001 and minimum of 33 per cent in 2009)<sup>3</sup>. There is a slight increase in the share of residential subsector as an employer: the number has increased for the period analyzed from 23 to 39 per cent despite the overall negative tendency. Possible explanation of this is an increase in the total number of companies in this sector (as seen from the figure 3.1) as a result of the overall increase in the demand for residential construction. But forecast for in this case is not promising: the number will go down as most of the companies have signed long term contracts with their employees.

As to the infrastructural sub sector, number of people employed was surprisingly stable over the period analyzed. The reason for that is the biggest contractors in this

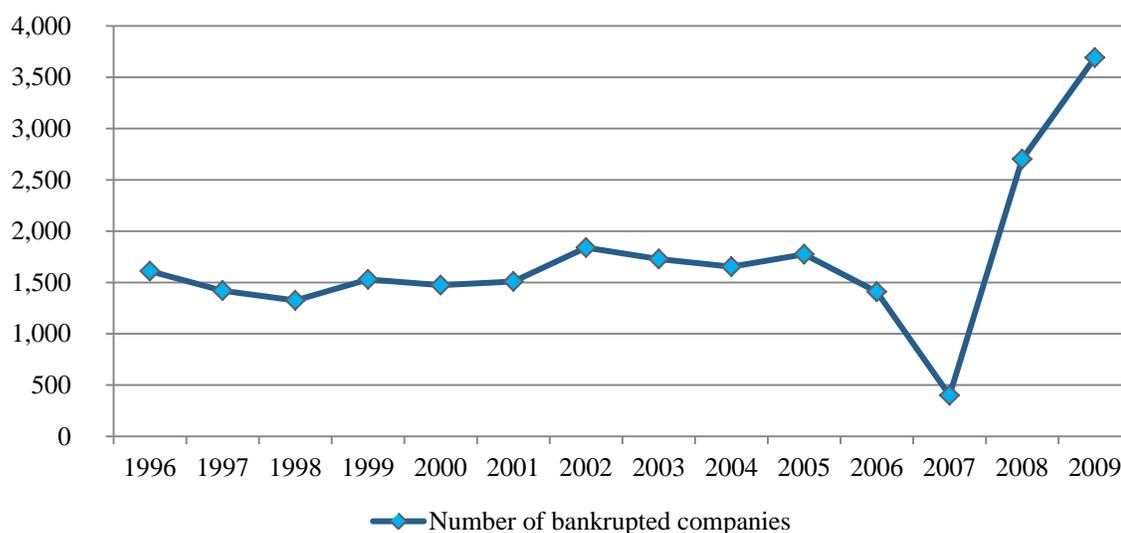
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<sup>3</sup> Note that in 2009 the percentage of people employed in non-financial construction sub sector has fallen above the average by almost 7 per cent

industry are governmental institutions or private contractors working for government which makes job positions more stable than on the market in average.

As to overall dynamics of the number of bankrupted entities in construction and materials industry (both listed and not listed on LSE), its development is presented in the Figure 3.4.

**Figure 3.4: Dynamics of the defaulted companies in construction and materials industry for the period 1996-2009 (delisted companies only)**



Author's calculations, data from ONS, 2010

In this case we've chosen slightly bigger time horizon because it is crucial for further analysis to understand the dynamics of bankruptcies in the selected industry. As we can see, the line for bankrupted companies is rather flat until 2005. Then sharp decrease in the number of bankruptcies in 2007 was caused by the increase in available financing (even financially unstable companies could get financing rather easily). Eventually the sources of financing depleted, companies, which were not able to generate positive cash flows, went bankrupt. This effect was increased by World recession, which caused even more companies in the sector to file for bankruptcy.

### **3.2 Altman Z-score Model**

The following part of the Master Thesis is devoted to computing Altman Z-score for selected companies from *Construction Sector* and *Household Goods Sector* in the United

Kingdom. Then we check the model's outputs, comparing them to the real number of bankruptcies in the mentioned sectors.

Altman Z-score model is widely recognized as one of the most popular tools for bankruptcy prediction, both by regulators and by financial institutions. That is why we chose the model to construct and to verify results, as the goal of empirical part of the thesis.

### **3.2.1 History & Methodology**

The efforts to identify variables (out of high number of accounting data) that could help foresee future stressed financial conditions of firms in advance are not new. One of the first rigorous models was developed by professor in New York University, famous economist A. Altman. In the work Altman (1968), he was the first to apply multiple discriminant analysis (MDA) for estimation of economics phenomenon. His initial idea was to empirically construct the linear model using the MDA, which before that had only been used in natural sciences, and to use it for prediction of corporate failures (Altman & Saunders, 1998).

Altman started with the sample of 66 publicly held companies. At **first step** he divided the sample into 2 sub-groups:

- Group 1 – companies, which filed for bankruptcy under Chapter 7 of the National Bankruptcy Act from 1946 through 1965;
- Group 2 – companies, which were defined as solvent.

Period of 20 year was taken as timeline for the analysis. In the best case scenario all the firms were supposed to be analyzed in the same time period. This would help the model to yield forward looking prediction of default probability. This was not possible at that time due to the data unavailability, however.

The sample of companies was rather heterogeneous. This heterogeneity stemmed from the fact that selected companies had been taken from different industries and were of different sizes (calculated from the value of assets). Due to this fact Altman paid extra attention to choosing non-bankrupted companies (Group 2). Although random sampling had been applied, further pre-selection was introduced as well: only companies with the asset size between 1 mil. and 25 mil. had got into the final range.

**Secondly**, having determined a subject sample, Altman proceeded to collect the

balance sheet data for the companies. After careful examination of all companies' financial statements, he determined 22 potential variables that might signal corporate failure. The reason for such a great number of variables was the sample heterogeneity – different variables could have different influence on bankruptcy probability for companies in the different industries (Altman, 1968).

**Thirdly**, in order to arrive to a final version of the model Altman tested different combinations of the 22 variables. He also tested the joint significance of different models and individual significance of each variable separately. The following discriminant function was eventually identified as the best performing model for bankruptcy prediction:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (13)$$

where:

$Z$  - cumulative Z-score;

$X_1$  - working capital/total assets ratio (percentage);

$X_2$  - retained earnings/total assets ratio (percentage);

$X_3$  - earnings before interest and taxes/total assets ratio (percentage);

$X_4$  - market value of equity/book value of total liabilities ratio (percentage);

$X_5$  - sales/total assets ratio (percentage).

The further explanation of the ratios included in the model are presented below.

- **Working Capital/Total Assets.**

This variable measures net liquid assets of the company relative to the total capitalization. Among the other liquidity ratios, this one has proven to be most relevant. It takes into consideration the liquidity side of the estimation in the most explicit way through the fact, that entities with constant operating losses will experience decrease in current assets with respect to total assets.

- **Retained Earnings/Total Assets**

This ratio expresses the amount of the earnings, which were reinvested back in the business with respect to total assets. Although, contribution of this ratio to total outcome

turned out to be very negligible, in measures the leverage of the company, which is also quite curtail for prediction of bankruptcy. That is why it cannot be omitted. On the other hand, it strongly discriminates against the age of the company: the younger firms will have a lower ration because they were not able to generate cumulative revenue, thus the older companies will has this ration somewhat higher (Altman, 1968). This makes sense because from the historical and business cycle perspective, younger companies are more likely to default than more experienced companies.

- **Earnings Before Interest and Taxes/Total Assets**

The following ratio is part of the profitability measurement indicators. It implicitly measures the level of productivity of company's assets. It also implies that well performing firms will have this ratio relatively high compared to distressed companies. Furthermore, insolvency in a bankrupt sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets (Altman 1968, p.7).

- **Market Value of Equity/Book Value of Total Liabilities**

This measure indicates the degree on devaluation of the company's assets with respect to the total book value of liabilities. Introduction of this ratio was quite innovative, because it takes into account open market data (commonly used ration before that was net worth/book value of the total debt). Just for that notice we would like to mention take more advanced models (e.g. KMV) are moving away from reliance on the financial statements data towards market data.

- **Sales/Total Assets**

The ratio above measures the ability of management of the company to operate in competitive environment. It illustrates how good the company is in generating additional revenue through increase in sales is. Although, this ratio has proven to be quite insignificant, it is a second most important most important model in the overall discriminant ability of the model.

According to Altman's (1968) classification, companies with Z-scores **above 3** are considered **creditworthy and financially stable**. Z-score values **between 1.81 and 2.99**

belong to the so-called “grey area” – firms which fall in within this range are considered **uncertain about credit risk exposure**. Entities with Z-score **below 1.81** are considered **failed or extremely close to default**. The lower bound for Z-score is 0. As to the upper bound, it was not defined in the model.

Having run the sample companies through the model, Altman documented that it had 72% accuracy in predicting bankruptcies two years prior to the event.

Being robust<sup>4</sup>, Altman Z-score model has become widely recognized and used by both practitioners and scholars. At some point it became one of the most widely used balance-sheet-based models. However, its initial inapplicability to privately-held and non-manufacturing companies (due to different balance sheet structure and composition) caused still further developments in order to fit particular needs and ownership structure.

In the further analysis we will compute the Altman Z-score model according to the specification given in (13).

### **3.2.2 Data**

In total, our examined sample consisted of 384 companies that were listed during the given period on London Stock Exchange (LSE)<sup>5</sup>. We restricted our choice subject to following criteria:

- We excluded companies with less than five years of business history. The purpose for this was to not include early failure or startup companies in the sample.
- We’ve also excluded companies that were registered or operated outside the territory of Great Britain.
- We required at least two years of stock price information prior to bankruptcy. The best case scenario is up to five years of stock price variable. All companies had to operate in construction and materials sector in United Kingdom.
- The sources of the financial data used for analysis were the annual reports of selected companies. The financial data used are annual and cover period of 2003-2008. To obtain the market value of the subject company included in the model, we took value of the company on the market as to the 31 December of each year (when

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<sup>4</sup> Type 1 error and Type 2 error were not high.

<sup>5</sup> Available at: <http://www.londonstockexchange.com>

stated in annual report). When not stated, we multiplied the number of shares outstanding on the average market price of the share for the given year.

- We have also eliminated companies with the asset value lower than £1 mil. and greater the £25 mil, not to have too significant outlier included.

Main problem with processing the data was connected to the difficulty with their extraction. In several cases the companies provided their financial statistics in misleading way, which make it difficult to comprehend them and extract them correctly. In some cases financial variables of companies were presented in different currencies (e.g. using euro). In these cases we converted currencies to pounds, using exchange rate 1€= 0.84£<sup>6</sup>. After that, summarization of data was straightforward.

In the end we selected 25 companies as a sample for analysis. 13 of them went bankrupt (or their shares were permanently delisted from LSE); 12 companies did not go bankrupt. All bankruptcies occurred in the year 2008.

**Table 3.1: List of selected companies from the construction & materials sector and Household Goods sector of Great Britain**

Company Name	Sector	Subsector	Market Cap. (£ml)
<b>BAGGERIDGE BRICK</b>	Construction & materials	Industrial Suppliers	753
<b>BARRATT DEVELOPMENTS</b>	Household Goods	Home Construction	1196
<b>BELLWAY</b>	Household Goods	Home Construction	987
<b>BEN BAILEY</b>	Construction & materials	Industrial Construction	917
<b>BERKELEY GROUP</b>	Household Goods	Home Construction	1073
<b>BOUSTEAD</b>	Construction & materials	Industrial Construction	758
<b>BOVIS HOMES GROUP</b>	Household Goods	Home Construction	578
<b>BPB</b>	Construction & materials	Industrial Construction	90
<b>BSS GROUP</b>	Construction & materials	Industrial Suppliers	296
<b>CARILLION</b>	Construction & materials	Industrial Construction	1056
<b>CREST NICHOLSON</b>	Household Goods	Home Construction	498
<b>ENNSTONE</b>	Construction & materials	Industrial Construction	762
<b>HAVELOCK EUROPA</b>	Construction & materials	Building Materials & Fixtures	108
<b>LOW &amp; BONAR</b>	Construction & materials	Building Materials &	94

<sup>6</sup> The exchange rate was taken as off 31 December, 2010 from London Stock exchange.

		Fixtures	
<b>MCALPINE(ALFRED)</b>	Construction & materials	Industrial Construction	526
<b>MCCARTHY &amp; STONE</b>	Construction & materials	Industrial Suppliers	863
<b>PERSIMMON</b>	Household Goods	Home Construction	1419
<b>PILKINGTON</b>	Construction & materials	Industrial Construction	561
<b>REDROW</b>	Household Goods	Home Construction	409
<b>ROK PROPERTY SOLUTIONS</b>	Household Goods	Home Construction	213
<b>TAYLOR WOODROW</b>	Construction & materials	Industrial Construction	468
<b>TRAVIS PERKINS</b>	Construction & materials	Industrial Suppliers	1770
<b>ULTRAFRAME</b>	Construction & materials	Industrial Construction	96
<b>WIMPEY(GEORGE)</b>	Construction & materials	Industrial Suppliers	268
<b>WOLSELEY</b>	Construction & materials	Industrial Suppliers	3520

Source: Author's compilation.

### 3.2.3 Results

In the following table we present results of Altman's Z-score model calculated for selected companies for each year during period from 2004 to 2008.

Table 3.2: Altman's Z-score calculation results for selected companies for the time period 2004-2008

Company Name	Year				
	2004	2005	2006	2007	2008
<b>BAGGERIDGE BRICK</b>	4.96	4.70	5.13	3.67	5.02
<b>BARRATT DEVELOPMENTS</b>	2.68	2.56	2.69	2.83	2.97
<b>BELLWAY</b>	4.00	2.63	5.21	5.03	4.90
<b>BEN BAILEY</b>	3.40	4.15	4.28	3.99	2.93
<b>BERKELEY GROUP HLDGS</b>	7.01	3.77	3.62	4.38	3.48
<b>BOUSTEAD</b>	3.19	3.00	2.82	2.88	2.58
<b>BOVIS HOMES GROUP</b>	1.80	1.65	1.51	1.58	1.66
<b>BPB</b>	1.28	1.25	1.23	1.37	1.31
<b>BSS GROUP</b>	3.52	2.92	2.46	2.73	2.62
<b>CARILLION</b>	2.51	2.36	2.31	2.29	1.76
<b>CREST NICHOLSON</b>	2.19	2.54	2.94	1.27	0.14
<b>ENNSTONE</b>	3.27	3.21	3.09	1.90	1.44
<b>HAVELOCK EUROPA</b>	5.20	5.06	4.13	3.27	1.38
<b>LOW &amp; BONAR</b>	13.52	12.65	15.03	4.02	6.61
<b>MCALPINE(ALFRED)</b>	3.04	2.81	2.72	2.70	1.65
<b>MCCARTHY &amp; STONE</b>	23.76	7.26	10.29	7.05	3.01
<b>PERSIMMON</b>	4.03	3.54	3.58	2.88	2.42

<b>PILKINGTON</b>	7.31	8.94	4.14	4.13	3.03
<b>REDROW</b>	0.75	0.80	1.23	1.26	1.30
<b>ROK PROPERTY SOLUTIONS</b>	2.59	1.74	1.78	1.77	1.76
<b>TAYLOR WOODROW</b>	3.52	2.92	2.46	2.73	2.62
<b>TRAVIS PERKINS</b>	2.80	1.80	1.76	1.78	1.38
<b>ULTRAFRAME</b>	3.24	2.89	1.80	1.80	1.76
<b>WIMPEY(GEORGE)</b>	4.35	4.01	1.76	1.79	1.45
<b>WOLSELEY</b>	9.45	10.45	5.56	3.46	1.30

Source: Author's calculations

Further, in order to test validity of Altman Z-score model, we compare number of real bankruptcies to that proposed by the model, thus determining number of correctly classified companies. For this purpose we are concerned with two questions:

- 1) Have Altman's Z-score model succeeded in correctly identifying those companies that went bankrupt in 2008? I.e. did these companies obtain Z-score values lower than 1.8?
- 2) Have Altman's Z-score model succeeded in correctly assessing companies that did not go bankrupt? I.e. did those companies obtain Z-score values higher than 3?

**Type 1 error** (Defined as percentage of companies that according to Z-score's prediction were reliable, but in reality they eventually bankrupted) provides answer to the first question:

Table 3.3: Altman Z score prediction statistics (bankrupted companies)

Year	All	Correctly Classified	Type 1 error	% correct
2004	13	4	9	33%
2005	13	5	8	41%
2006	13	7	6	58%
2007	13	9	4	75%
2008	13	13	0	100%

Source: Author's calculations

In the year 2008 Altman's Z-score model correctly classified all bankrupted companies. One year in advance (based on the firms' data from 2007) the model successfully marked 75% of defaulted companies as bankruptcy candidates. When calculated from 2006 data, the model correctly detected 58% of the firms that defaulted in 2008 as heading for bankruptcy.

Thus, our results suggest that the longer time period between calculation of Z-score and bankruptcy, the larger is Type-1-error of the model. E.g. when Z-scores of firms are calculated according to 2004 data, as much as 77% of bankrupted companies<sup>7</sup> are not detected in bankruptcy range (Z-score below 1.8). As the time lag increases, the percentage of type 1 error also increases.

**Type 2 error** (Defined as percentage of companies that according to Z-score's prediction were candidates for bankruptcy, but in reality did not file for default) provides answer to the second question:

**Table 3.4: Altman Z score prediction statistics (non-bankrupted companies)**

Year	All	Correctly Classified	Type 2 error	% correct
2004	12	12	0	100%
2005	12	12	0	100%
2006	12	12	0	100%
2007	12	12	0	100%
2008	12	12	0	100%

Source: Author's calculations

In this respect Altman Z-score's<sup>8</sup> results proved robust. In all considered time horizons there was no firm wrongly detected as heading for default. Model was able to fully correctly classify creditworthy companies.

Altman Z-score model performed accurately in a sense that it indicated the potentially unstable companies at least two years before the bankruptcy took place. Accuracy of prediction decreases with increased time horizon. In a modern dynamic financial world we consider this characteristic not surprising, however. The model exhibited ability to foresee more than 50% of bankruptcies 2 years in advance (at the same time with no error committed in identification of "healthy" firms), which suggests its good general applicability even nowadays. It can be utilized as helpful tool not only from portfolio manager's point of view, but can produce quite accurate information also for the management of a company, on which vital internal and external related decisions could be made.

Still, it would not be sensible to use Altman Z-score as the only tool for assessing

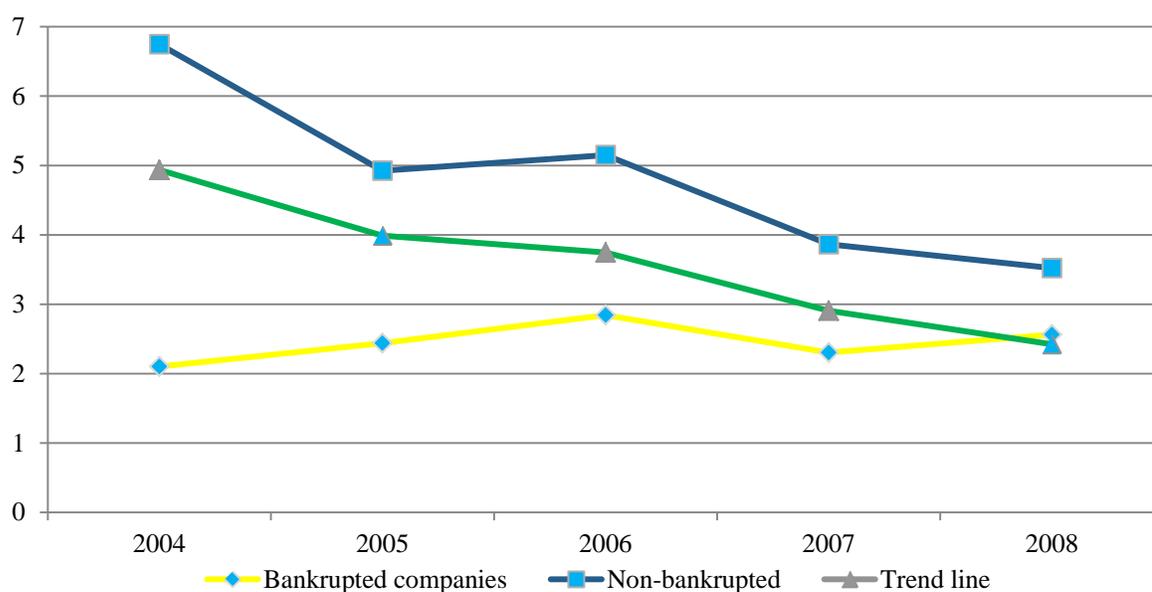
<sup>7</sup> Bankrupted in the year 2008.

<sup>8</sup> Calculated under specification given in (13)

creditworthiness of companies itself, especially in decisions about granting longer-term credits.

Another characteristic feature of obtained results is decreasing trend in Z-score values for the sample of examined companies as a whole. The following chart captures the movement of average Z-scores for both groups of bankrupted and non-bankrupted companies from 2004 to 2008.

**Figure 3.5: Development of the average value of a Z-score for selected companies over the period 2004-2008**



Source: Author`s calculations

The highest average Z-score for both bankrupted and non-bankrupted companies in the period analyzed was in the year 2004 (value of **4.93** points), then it kept decreasing till the end of observed period in 2008 (value of **2.56** points). Altman (1983) suggested that aggregated Z-score may vary over time also as consequence of exogenous economic evolution of whole sector, which in itself may influence creditworthiness of companies as a whole group. That is why we take downward trend of Z-scores in our sample as a sign of the possible recession in the industry.<sup>9</sup>

<sup>9</sup> Practical consequence of such persistently decreasing Z-score over time could be (ceteris paribus) significant changes in investment policies of financial institutions (including banks). Because such policies are

It is documented that Z-score tends to be higher during bullish market, while being lower during bearish markets (Gerantonis and Vergos, 2009). Justification of this empirical finding is usually following: Bullish markets give the ability to survive even to financially distressed companies. The reason for that is that during bullish markets, financially distressed companies are able to raise additional (relatively cheap) financing from financial market or banks. This gives them an opportunity to finance activities and cover the need of capital. However, due to not being able to generate positive operating cash flow, this type of financing could only work as a temporary measure. As a result, financial problems will appear again in worse economic condition, when companies will not be able to raise financing and they will gradually become insolvent or go bankrupt. Therefore the ability of pre-bankrupted companies to raise capital in bullish markets does not have any significant influence on their financial stability over the longer period of time.

***Quick note: Comparison of the Altman (1983) calculation result and our models yields.***

*During his estimation of Z-score model ability to predict default cases on the sample of 33 bankrupted companies Altman found that the prediction accuracy of the model varies for longer prediction horizons such as four- and five-year horizons. Accuracy fluctuates from 95% for 1-year and 72% for 2-year prediction horizon, to 48% for 3-year, 29% for 4-year and 36% for 5-year horizon. Our results are presented in the above tables to compare to.*

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not as flexible as dynamic market conditions, their accommodation may be lagged, and the institutions may end up suffering losses due to substantial Z-score change if not being able to react appropriately.

### 3.2.4 Testing variables significance

As we have determined in sub section 3.2.3, Altman Z-score model is quite reliable when it goes down to prediction of corporate failures. In line with the prediction ability of the Altman Z-score model, the question of the particular interest of this Master thesis is: what the influence (sign of relationship) between dependent variable (probability of default) and explanatory variables (accounting data)? In other words we want to examine which part of the variation in probability of default we are able to explain using the specification (explanatory variables), used by the Altman Z-score model.

Firstly, let's obtain the economic model, which would be used as a baseline for analysis. Because we are analyzing the Altman Z-score model, the initial economic model will have a similar specification. Therefore, the economic model which will become the theoretical framework for analysis is the following:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (14)$$

where:

$Z$  - cumulative Z-score;

$X_1$  - working capital/total assets ratio (percentage);

$X_2$  - retained earnings/total assets ratio (percentage);

$X_3$  - earnings before interest and taxes/total assets ratio (percentage);

$X_4$  - market value of equity/book value of total liabilities ratio (percentage);

$X_5$  - sales/total assets ratio (percentage).

From the theoretical model, described by Eq. 14 we are able to form the econometric model, which would be used for further analysis. Therefore, the econometric model is the following:

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + u_t \quad (15)$$

where:

$Z$  - cumulative Z-score (dependent variable);

- $X_1$  - working capital/total assets ratio (percentage) (explanatory variables);
- $X_2$  - retained earnings/total assets ratio (percentage) (explanatory variables);
- $X_3$  - earnings before interest and taxes/total assets ratio (percentage) (explanatory variables);
- $X_4$  - market value of equity/book value of total liabilities ratio (percentage) (explanatory variables);
- $X_5$  - sales/total assets ratio (percentage);
- $\beta_0$  - intercept coefficient;
- $\beta_1 \cdots \beta_5$  - slope coefficients (coefficients of explanatory variables)
- $u_i$  - stochastic disturbance term (account for variables, not included in the equation).

On the first step of our analysis we will use Z-score and accounting data for a year 2008 (actual year of filing for bankruptcy). We'll take advantage of the Ordinary Least Squares (OLS) estimation method in the very beginning in order to build the framework for further testing. Then we will see if OLS results are trustworthy by running number of tests. If the results of the testing will be not satisfactory (implying data problems, e.g. heteroscedasticity), we will try to correct the problem by using appropriate techniques.

***Quick note: on the OLS estimation***

*The ordinary least squares method is a formal technique to the approximate system of equations, in which the number of equations exceeds the number of unknown variables (so called over determined systems) and the residuals are linear in all unknowns. The essence of the OLS approach is based on minimizing the sum of squares of the stochastic error term, which occurs while solving every single equation separately.*

*So having the initial regression as the following:*

$$Z_i = \beta_{0,i} + \beta_{1,i}x_{1,i} + \beta_{2,i}x_{2,i} + \beta_{3,i}x_{3,i} + \beta_{4,i}x_{4,i} + \beta_{5,i}x_{5,i}$$

*The sum of square residual minimization is done through estimation of slope and intercepts coefficients of the regression line through the following formulas:*

$$\hat{\beta}_1 = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$\hat{\beta}_0 = \bar{y} - \hat{\beta}_1 \bar{x}$$

*In our case all the relevant calculation were performed in statistical software Gretl. However they could also be made in Microsoft Excel software.*

Therefore, by using the Gretl software, one of the most sophisticated and trustworthy statistical software for data analysis, we have managed to obtain the following results. (Estimation results are presented in the in the Table 3.5 below)

**Table 3.5: OLS model estimation results using 25 observations for the year 2008. Dependent variable: Default Probability**

	<b>coefficient</b>	<b>std. error</b>	<b>t-ratio</b>	<b>p-value</b>
<b>const</b>	0.127257	0.290384	0.4382	0.6662
<b>Working_capital</b>	0.0660942	0.341234	0.1937	0.8485
<b>Retained_earnin</b>	1.96591	0.310797	6.325	4.53e-06 ***
<b>EBIT_total_asse</b>	0.634682	0.374443	1.695	0.1064
<b>Market_value_of</b>	0.631064	0.0530345	11.90	2.99e-010 ***
<b>Sales_Total_ass</b>	0.819898	0.204980	4.000	0.0008 ***

<b>Mean dependent var</b>	2.423884	<b>S.D. dependent var</b>	1.421139
<b>Sum squared resid</b>	3.906806	<b>S.E. of regression</b>	0.453455
<b>R-squared</b>	0.919400	<b>Adjusted R-squared</b>	0.898189
<b>F(5, 19)</b>	43.34615	<b>P-value(F)</b>	9.64e-10
<b>Log-likelihood</b>	-12.27152	<b>Akaike criterion</b>	36.54303
<b>Schwarz criterion</b>	43.85629	<b>Hannan-Quinn</b>	38.57142

Source: Author's calculations

Before we start the actual interpretation of results, let us first make sure the results of the estimation above are trustworthy. In case of the data being analyzed, we may face heteroscedasticity issues, which could make the outcomes of our estimation biased and inconsistent.

Heteroscedasticity implies existence of correlation between explanatory variables and stochastic disturbance term. The existence of heteroscedasticity comes with the violation of basic OLS assumption and therefore incorrectness of the estimation. In the common literature (see Baltagi, 2001) there are two ways how to test for presence of heteroscedacticity: Breush-Pagan Test and White Test. Let us first apply Breush-Pagan test

and interpret the results.

As it was already mentioned above, Breusch-Pagan test is designed to detect any linear form of heteroskedasticity and is based on the following hypotheses:

**Hypotheses:**

Under the null hypothesis there is no correlation between explanatory variables and disturbance term ( $H_0: \beta_i=0$ )

Under  $H_A$  the correlation between explanatory variables and disturbance term is present (at least one  $\beta_i$  no equal to 0). ( $H_A: \beta_i \neq 0$ )

Test statistics in this case is described as a simple F-test:

$$F = \frac{R_u^2 / k}{(1 - R_u^2) / (n - k - 1)} \sim F(k, n - k - 1) \quad (16)$$

Likely for us this type of test could be calculated for us in Gretl. Therefore, the results of the test are presented in the Tables below:

**Table 3.6: Breush-Pagan test statistics results for the OLS model 1**

Breusch-Pagan test for heteroskedasticity:

Null hypothesis: heteroskedasticity not present

Test statistic: LM = 8.82111

with **p-value** = P(Chi-Square(5) > 8.82111) = 0.116416

**Source: Author's calculations**

Grounding on the test results, presented in the Table 3.1 we can claim, that heteroscedasticity is present. The sign for that is the low p-value (which indicated probability of data being homoscedastic) of 11 per cent. That is why we can reject the null hypothesis (homoscedasticity of the sample). Thus, based on the Breush-Pagan test results we can conclude, that heteroscedasticity is present.

Next, let us turn to White's test. White's test is based on auxiliary regression with squared residuals as dependent variable and regressors (explanatory variables) given by the regressors of the initial model, their squares and their cross products. Although it is based on the same hypotheses and usually performs results, quite similar to Breush-Pagan test, let

either support or doubt the results, obtained in the previous testing. The results of the White's test estimation are presented in the Table below.

**Table 3.7: White's test statistics results for the OLS model 1**

White's test for heteroskedasticity: Null hypothesis: heteroskedasticity not present Test statistic: $LM = 22.8295$ with <b>p-value</b> = $P(\text{Chi-Square}(20) > 22.8295) = 0.297243$
--

**Source: Author's calculations**

As we can see from the Tables 3.4, the White's test obtains results, somewhat better than Breush-Pagan test (probability of homoscedasticity is 29 per cent). But this is way below 50 per cent cut-off line.

As a conclusion on heteroscedasticity testing we may claim that it is present, based on the results of both Breush-Pagan and White's test.

Subsequently we have determined that heteroscedasticity is present in our case. Therefore, OLS estimates, presented in the Table 3.2 are not consistent and cannot be used. If we need to estimate the model knowing that heteroscedasticity is present in the data, we can use the following estimation methods:

- Use robust standard errors for OLS estimation;
- Use Logit model;
- Use Feasible Generalized Least squares estimation (FGLS) in particular weighted least squares (WLS).

We cannot consider the usage of both robust standard errors and Logit model in our case due to relatively small data sample (25 companies). The only option left is to use WLS and see if we can get significant results.

According to Baltagi, 2001 feasible generalized least squares estimation is one of the most efficient ways of dealing with heteroscedasticity problem. Although it may seem rather complicated at the first glance, its logic is quite straightforward. Let us go through the WLS method step by step applying our data sample.

Firstly, we run the OLS estimation on the data set of 25 companies, as we did it in

the beginning of this chapter. The models specification, used for OLS estimation is exactly the one, presented by Eq. 15.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + u_t \quad (17)$$

where:

$Z$  - cumulative Z-score (dependent variable);

$X_1$  - working capital/total assets ratio (percentage) (explanatory variables);

$X_2$  - retained earnings/total assets ratio (percentage) (explanatory variables);

$X_3$  - earnings before interest and taxes/total assets ratio (percentage)

(explanatory variables);

$X_4$  - market value of equity/book value of total liabilities ratio (percentage)

(explanatory variables);

$X_5$  - sales/total assets ratio (percentage);

$\beta_0$  - intercept coefficient;

$\beta_1 \cdots \beta_5$  - slope coefficients (coefficients of explanatory variables)

$u_t$  - stochastic disturbance term (account for variables, not included in the equation).

We also use Gretl software to proceed. After running the regression we record squared residuals of this estimation.

Secondly, we use logarithmic form of residuals, obtained in the first step, as dependent variables for the OLS regression with the same explanatory variables. Therefore, the model to be estimated is the following:

$$\log(e_i) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + u_t \quad (18)$$

where:

$\log(e_i)$  - Logarithm of squared residuals (dependent variable);

$X_1$  - working capital/total assets ratio (percentage) (explanatory variables);

$X_2$  - retained earnings/total assets ratio (percentage) (explanatory variables);

$X_3$  - earnings before interest and taxes/total assets ratio (percentage) (explanatory variables);

$X_4$  - market value of equity/book value of total liabilities ratio (percentage) (explanatory variables);

$X_5$  - sales/total assets ratio (percentage);

$\beta_0$  - intercept coefficient;

$\beta_1 \cdots \beta_5$  - slope coefficients (coefficients of explanatory variables)

$u_i$  - stochastic disturbance term (account for variables, not included in the equation).

The estimation is performed in Gretl as well. As a result of this estimation we record fitted values of  $\log(e_i)$ .

Thirdly, we use the exponential of fitted values of dependent variables, recorded in the previous step, in order to obtain pre-weights, necessary for FGLS estimation.

$$preWeights = \exp(\widehat{\log(e_i)}) \quad (19)$$

Finally, we use pre-weights, obtained in the third step in order to determine final weights to be used in WLS estimation.

$$Weights = \frac{1}{preWeights} \quad (20)$$

The results of the WLS estimation performed as step-by-step shown above, are presented in the Table below.

Table 3.8: WLS, using observations 1-25. Dependent variable: Default\_Probabi

Variable used as weight: weight

	coefficient	std. error	t-ratio	p-value
const	-0.190903	0.139034	-1.373	0.1857
Working_capital	0.461120	0.229730	2.007	0.0592 *
Retained_earnin	2.10988	0.290477	7.264	6.82e-07 ***
EBIT_total_asse	0.589342	0.341692	1.725	0.1008
Market_value_of	0.602736	0.0408831	14.74	7.46e-012 ***
Sales_Total_ass	1.06180	0.0823195	12.90	7.58e-011 ***

Statistics based on the weighted data:			
Sum squared resid	121.1677	S.E. of regression	2.525321
R-squared	<b>0.961662</b>	Adjusted R-squared	0.951573
F(5, 19)	95.31781	P-value(F)	8.80e-13
Log-likelihood	-55.20221	Akaike criterion	122.4044
Schwarz criterion	129.7177	Hannan-Quinn	124.4328

Source: Author's calculations

In order to see if the WLS results are consistent and there is no correlation between explanatory variables and stochastic disturbance term we will run the F-test with the following test statistics:

$$F = \frac{R_u^2 / k}{(1 - R_u^2) / (n - k - 1)} \sim F(k, n - k - 1) \quad (21)$$

where:

$R_u^2$  -unadjusted R –squared (calculated for us in Gretl and highlighted in Table 3.5)

F-test implies the following hypotheses:

Under the null hypothesis there is no correlation between explanatory variables and disturbance term;

Under  $H_A$  the correlation between explanatory variables and disturbance term is present (at least one  $\beta_i$  not equal to 0).

Likely, the F-test is calculated for us in Gretl as well. That is why all we need to do is to compare the value of the F-statistics, presented in Table 3.5 with the critical value of the F-statistics, presented in statistical tables. If the value of the F-statistics, calculated in Gretl exceeds the appropriate critical value for given degrees of freedom. Therefore the necessary condition for homoscedasticity is the following:

$$F(v_1, v_2) < F(\text{critical}) \quad (22)$$

where:

$v_1$  - degrees of freedom in the numerator;

$v_2$  - degrees of freedom in the denominator;

$F(\text{critical})$  - critical value of F-statistics, taken from the statistical tables.

Thus, we have that:

$$95.31781 > 4.17^{10} \quad (23)$$

Therefore, due to the fact, that condition, mentioned in the Eq. 21 does not hold, we assume that heteroscedasticity is still present. Despite the fact, that the level of heteroscedasticity has decreased substantially, we still cannot use WLS estimation results due to the fact, that they will be biased and inconsistent.

Thus, using available data we are not able make any feasible conclusions with respect to what is the influence of accounting data on prediction of corporate failures. The only reliable estimation of prediction ability of Altman Z-score model is historic simulation, used in the sub section 3.2.3.

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<sup>10</sup> One 1 per cent probability level ( $\alpha = 0.01$ )

## 4. Conclusion

*Classification of risks, risk measurement, risk exposure and risk management*; risk has always belonged to the key areas of interest for the financial institutions. Current market conditions, the increase in the number of financial operations worldwide, commercial banks' involvement in the overall expansion of the GEO coverage of financial institutions; all that made questions of risk assessment in modern times still more prominent. In order to find the reasonable equilibrium between risk undertaken and profit received, numerous risk measurement methods have been, and are still being, developed. This diploma thesis has got an aspiration to contribute to this large and interesting topic.

In the first chapter of the thesis we provided overview of current state of knowledge in this field, following classification of risks provided in Capital Accord of Basel Committee on Bank Supervision. Along with definitions for each type and sub-type of risk of financial institutions we briefly described key principles of their management.

In the second chapter we focused attention on the *credit risk* assessment, as the most important type of risk that commercial and investment banks are exposed to. We have surveyed principal techniques and models of credit risk measurement, both modern and traditional. We documented the evolution of models from the "subjective" risk-evaluation-models (such as 5 C's, expert systems and scoring models), to the up-to-date sophisticated complex models that embrace large number of risk factors and utilize modern computational software (Value-At-Risk, Credit metrics, Macro-Simulation Approach etc.). Despite different levels of complexity, there exists high degree of interconnection between traditional and modern approaches.

In the practical part of the thesis, chapter 3, we computed Altman's Z-score for sample of 25 companies from *Construction & Materials sector* and *Household Goods sector* in United Kingdom, over period 2004 – 2008. We used model specification as in Altman (1968). Sources of the data were balance sheets of companies. Companies of the two sectors were selected out of firms listed on London Stock Exchange.

Underlying motivation was the question: Would be the model able to adequately capture the probability of default for individual financial institutions (even in modern dynamic world)? After comparing obtained Z-scores to real numbers of bankrupted/non-bankrupted companies (and computing type 1 and type 2 errors), the answer seems to be

“Yes”. The model did excellently from the point of view of “false-negative” identified companies, where it had got 100% match. As to the number of “false-positive” identified companies, the results of the model were less convincing, though. Based on the balance-sheet data from one year prior to (real) bankruptcy, the model correctly identified 75% of firms as bankruptcy candidates. With longer time lag, ability of the model to foresee bankrupted firms decreased. It suggests that using Altman’s Z-score as *the only* tool for making decisions about financial soundness of firms (especially for longer time horizons) might not be sensible.

Another characteristic of the obtained results that we consider interesting is the decrease in the average Z-score throughout the whole period of 2004-2008.

The second underlying motivation was to estimate the influence of each variable included in the model on the final outcome – Z-score. This would allow us to determine the value of each input of the model (in our case each accounting variable) and make conclusions with respect to possible ways of improvement of the model (e.g. changing specification by including or excluding various ratios). However, due to the sample-size limitation we were unable to run Logit regression. Furthermore, when testing assumptions for OLS, we encountered heteroscedasticity problem. Numerous data-transformations were afterwards employed to try to correct for heteroscedasticity. Sadly, in spite of transformations made, neither WLS nor FGLS methods were able to get rid of the heteroscedasticity problem entirely. Thus, out of the data, we did not reach trustworthy conclusions about the prediction ability and goodness-of-fit of the model.

To sum up the empirical part of the thesis, Altman’s Z-score under given specification seems to have passed the test of rightly distinguishing stressed and healthy companies. With longer time horizons model’s detection of healthy ones should be taken with appropriate caution, however. Another point of interest was testing significances of the explanatory variables of the model. Because of data limitations we were not able to estimate it. This question thus remains open for further research with more suitable datasets.

Subchapter 3.1 provides characteristic and evolution of Construction & Materials sector in United Kingdom.

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## *Appendixes*

## Appendix 1

**Table A.1: Comparison of main risk categories (Based on Elder, 2006 and Kiraly, 2005)**

	Market Risk	Credit Risk	Operational Risk
Measure of exposure (Yes/No)	Yes	Yes	Difficult to determine exposure
Risk Factors	Interest rates, foreign Exchange rate fluctuations, share price fluctuation, commodity price volatility	Probability of default (PD); Loss given default (LGD); Exposure at Default.	Probability of event Loss given event
Approaches of risk measurement	Value at Risk (VAR) Stress Testing Economic capital	Scoring/rating systems PD/LGD models Economic capital	Op Risk VaR, Economic capital
Reliability of measurement	Good	Acceptable	Insufficient
Risk management techniques	Limits, balance sheet matching, hedging with derivative positions	Limits, intake of collaterals, credit portfolio, securitization, credit derivatives	Process management, system development, insurance, application of risk transfer mechanisms

Source: Benedek, 2007.

## Appendix 2

Table A.2: Example of a Mortality table

	1	2	3	4	5	6	7	8	9	10
AAA Marginal	0.00%	0.00%	0.00%	0.00%	0.03%	0.00%	0.00%	0.00%	0.00%	0.00%
AAA Cumulative	0.00%	0.00%	0.00%	0.00%	0.03%	0.03%	0.03%	0.03%	0.03%	0.03%
AA Marginal	0.00%	0.00%	0.35%	0.19%	0.00%	0.00%	0.00%	0.00%	0.03%	0.02%
AA Cumulative	0.00%	0.00%	0.35%	0.54%	0.54%	0.54%	0.54%	0.54%	0.57%	0.59%
A Marginal	0.00%	0.00%	0.02%	0.07%	0.03%	0.08%	0.05%	0.09%	0.06%	0.00%
A Cumulative	0.00%	0.00%	0.02%	0.09%	0.12%	0.20%	0.25%	0.34%	0.40%	0.40%
BBB Marginal	0.12%	0.48%	0.55%	0.59%	0.56%	0.58%	0.72%	0.15%	0.05%	0.26%
BBB Cumulative	0.12%	0.60%	1.14%	1.73%	2.28%	2.85%	3.55%	3.70%	3.75%	3.98%
BB Marginal	0.96%	1.65%	3.15%	1.54%	2.15%	0.95%	1.65%	0.45%	1.75%	3.75%
BB Cumulative	0.96%	2.59%	6.50%	7.12%	9.12%	9.98%	11.47%	11.87%	13.41%	16.66%
B Marginal	1.60%	4.94%	5.95%	6.72%	5.94%	4.15%	3.12%	2.10%	1.65%	0.85%
B Cumulative	1.60%	6.46%	12.03%	17.85%	22.73%	25.94%	28.25%	29.76%	30.92%	31.51%
CCC Marginal	4.35%	13.26%	14.84%	8.15%	3.02%	9.15%	4.56%	3.26%	0.00%	4.15%
CCC Cumulative	4.35%	17.03%	31.00%	36.62%	38.53%	44.15%	46.70%	48.44%	48.44%	50.58%



**Hypothesis:** Taking into consideration the research question, we assume that there were certain drawbacks in the risk management in Ukrainian banking system, that in its turn caused misevaluation of the level of riskiness of activities and enormous losses both to the banks within the country and their subsidiaries abroad

**Methodology:** I will attempt to answer these two questions, using (a) contemporary as well as past evidence and information on the activity of the Ukrainian banking system, (b) logical arguments based on existing literature and theories, and (c) applying method based on fuzzy-neural-network and also other methodology used both in Ukrainian financial institutions and those, that are common Worldwide which is however subject to reasonable availability of suitable data.

## Basic outline

1. Introduction
2. Risk management – general theory
  - 2.1 Classification of risks
  - 2.2 Risk assessment - Traditional and modern approaches
3. Risk assessment as a part of the risk management process
  - 3.1 Models and methodology of risk assessment
  - 3.2 Valuation of assets including risk-parameters
4. Risk assessment and its influence on the decision-making process  
in financial institution
5. Risk measurement models: evaluation and assessment
6. Conclusions

**Key words:** Credit risk, Liquidity risk, index-methods, fuzzy-neural-network

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