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MASTER THESIS

CREDIT RISK MEASUREMENT:

The case study of Mongolian Small and Medium sized firms

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Abstract

This thesis presents credit risk measurement approaches and some empirical results of predicting firm's failure by using various financial ratios. It aims to re-examine Altman's Z-score model and build a comparable method by logistic regression, a credit scoring model technique. The small and medium sized enterprises' empirical data used in the research work is provided from a Mongolian commercial bank. We analyzed forty two firms' financial statements, including bankrupted and non-bankrupted firms, for the period of 2007-2008. At first, financial ratios of selected sample have been analyzed through Altman's Z-score model. Overall, prediction accuracy of Altman Z-score model was significantly high, 71 percent. In terms of logistic regression method, we estimated fifteen financial ratios through the model and come to conclusion that two ratios, namely cash to total asset ratio and retained earning to total asset ratio, are significant predictor for firm's bankruptcy in Mongolian SMEs. If we compare the prediction power of the two methods, model derived from logistic regression is slightly lower than in Altman Z score model.

Keywords: Credit Risk measurement, bankruptcy, Altman Z score, logistic regression

Introduction

Risk management is core concept in bank and financial sector because it has substantial effect not only on the behavior of financial institution, but also economy of a country as well as entire world. For that reason, the risk management issue is paid more and more attention in the every level of any organization over the world. In addition, as financial industry becoming more competitive as well as complex, bankers and financial managers have been shifted away from consideration on profit or spread towards to risk pricing. In other words it is not only insufficient to earn high return rate on an investment; but also important question is if the earned return compensates the banks properly for the risk that is assumed. That is why, the quantifying risk and finding optimal mix between taking risks, maximizing returns by creating own capital provisions are crucial for financial world.

However the risk management is broad and complex process, it is defined simply as: *''the identification, assessment, and prioritization of risks followed by coordinated and economical application of resources to minimize, monitor, and control the probability or impact of unfortunate events or to maximize the realization of opportunities"*. Main risks faced by typical financial institutions fall into the broad categories-namely credit, market, liquidity and operational risks.

Among the risks bank could face, credit risk is fundamentally the most important and credit risk management issues have been evolved dramatically for last twenty years by driving some forces: competition on financial market is getting more severe, increased number of bankruptcy over the world declining value of real assets in many markets and a dramatic growth of off-balance sheet instrument with inherent default risk exposure, including credit risk derivatives (EdwardI.Altman, 1998).

In parallel with the developments in credit risk management theories, Basel Accord provides a definite and broad framework to manage credit risk. Basel II defines a credit risk internal rating system at paragraph 394 "it comprises all of the methods, processes, controls, and data collection and IT systems that support the assessment of credit risk, the assignment of internal risk ratings and the quantification of default and loss estimates" (BCBS, 2006). To construct an internal rating system banks can employ variety of statistical and market approaches which are developed under statistical and financial theories. In order to implement this, banks must meet certain requirements which are described in Basel II accord or regulatory body. Taking into account the fact that the internal rating system is a broad and complex system, we will limit us as methods for assessment of credit risk.

Aims of the master thesis are:

- At first, to review the literature around theoretical and empirical developments in the commercial banking credit risk management methodologies.
- Secondly, to apply appropriate probability default quantification model for SMEs' data set taken from a commercial bank of Mongolia and to examine the most influential risk factors which explains probability default.

The thesis is organized as follows:

In the next chapter, we will present credit risk definition, its major drivers and internal applications of credit risk quantification and explain specific aspect of credit risk measurement. Also, Basel accord overview and its retail exposure treatment will be discussed briefly. Second chapter is devoted to study traditional and latest credit risk measurement approaches. We will introduce main assumptions and logic behind of the models and attempt to conclude in terms of suitability and availability for emerging economy. Third chapter covers Mongolian banking sector analysis and credit risk management development.

Fourth chapter displays empirical application and results. We re-examined Altman Z score model for Mongolian small and medium sized firms. After doing this, next goal was to develop a model using logistic regression credit scoring method. In final chapter, the thesis is concluded.

Chapter1. Credit risk management and Basel Accord overview

Credit risk management is one of the main issues of modern financial institutions with recent dramatic growth in retail credit and increase in volatility of real economy. This is the risk of financial loss due to the applicants' failure to pay the credit back. Financial institutions and banks are trying to deal with the credit risk by determining capital requirements according to the risk of applicants and by minimizing the default risk with using the statistical techniques to classify the applicants to "good" and "bad" risk classes.

On the other hand Basel Committee on Bank Supervision introduces three main categories of risk that face banks and financial institutions: credit risk, market risk and operational risk. From the point of view of regulator, the risks are major factors for banks therefore banks must keep enough capital provision to cover potential losses from the risks. According to the Committee credit institutions and banks have the opportunity to use standard or internal rating based (IRB) approach when calculating the minimum capital requirements. We will discuss credit risk definitions, characteristics and overview of Basel Accord in following sections of this chapter.

1.1 Credit risk definition and characteristics

There are various definitions of credit risk in literatures.

Most common definition described by Basel Committee on Bank Supervision is: "credit risk is the "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). Alternatively, credit risk is defined as the risk that "...unexpected change in a counter-party's creditworthiness may generate a corresponding unexpected change in the market value of the associated credit exposure" (Sironi & Resty, 2007).

The definitions consist of three core concepts that should be discussed in a bit more detail. First of all, credit risk is not constrained only to an obligor's default and loss resulting from its insolvency, but also covers the risk arising from the deterioration in credit quality, which is expressed by downgrading or upgrading of its credit rating. Secondly risk as an unexpected event which means that in order to be known as risk the variations of counterparty's creditworthiness must be unexpected. If a bank has issued a loan knowing that the counterparty will suffer a future deterioration in quality (profitability, solvency, liquidity, etc.), that deterioration will have been suitably evaluated and factored into the decision to grant the loan and the pricing process.

Third concept that must be considered is credit exposure. In the definition we discussed about market value of credit exposures. But most of credit exposures are recorded in banks books at historical value not at market value. Correct measurement of credit risk requires economic value of exposures that is willing to be exchanged in a secondary market.

Common credit risk types that are described in literatures as follows:

Default risk: this is commonly understood as the unwillingness or inability of an obligor to payback his debt in timely manner and quantified by probability of default (PD) that takes value between 0 and 1. The default definition can seriously impact on the PD and other components of credit risk quantifications while minor difference among default estimation stem from methods used.

Migration risk: as discussed above, it is risk that is connected with deterioration of counterparty's creditworthiness. It is known as downgrading risk when borrowers has been rated by public credit rating and the institution that issued the grade might downgrade the counterparty.

Spread risk: this is the risk associated with arise in the spreads required of borrowers by the market; in the event of increased risk aversion by investors, the spread associated with a given probability of default may increase; in such a case the market value of the securities declines ,without any reduction in the issuer's credit rating.

Recovery risk: indicates the risk that actual estimated recovery rate that is for a insolvent counterparty will be less than the rate that is estimated originally. This is could be because of the liquidation process takes longer time than estimated or value the counterparty is liquidated is lower than anticipated and so on.

Pre-settlement risk: the traditional view of credit risk refers to the potential loss due to the counterparty's default during the life of the transactions, i.e., a default on a loan, bond or a failure to make payment on derivatives. This risk persists for long period, usually in years, starting from the contract sign till the transaction is settled.

Country risk: it refers the risk a counterparty is not able to pay its obligation due to political and legislative factors e.g. the introduction of foreign exchange constraints, which prevent it from repaying its debt.

Based on the risk categorization that is classified by major risk drivers (default, downgrading, recovery rate and etc) and nature of credit exposure, credit risk measurement models and quantification techniques are developed and we will analyze further chapters as core subject of this paper.

1.2 Credit risk management process

Credit risk measurement and quantification models are vital for quantifying, collecting and managing risks within the whole organization across branches, business lines and geographical areas. The results of credit risk management techniques have crucial roles in bank's risk management and performance measurement processes, customer analysis, pricing, active portfolio management and capital structure decisions. Moreover, credit risk management process can from institution to institutions depending on the financial institution's size, operational structure, customer segmentation and management policies. There are general processes however, that are suggested as general rule. We will review here the credit risk management main steps as described in (Van Gestel & Baesens, 2009):

Identification: The process starts with an identification of all possible risks. It is a process to analyze all sources and requires deep knowledge of financial products that would enable to reveal the sources of potential risk and threats.

Measurement: Once the risk is identified, quantification or the measurement becomes the next step. That is, to determine the actual probability of default, loss given default and their sensitivity to changes in underlying factor movements. Statistical analysis of historical events and data are essential for measuring risk and when they are not adequate and limited, banks utilize theoretical models and human expert knowledge to measure risks.

Treatment: It is rational for banks to avoid risk that has potential harm exceeding the returns from investing in it, while medium or small risks can be further transferred (contract with insurance companies, enter credit default swaps contracts), reduced (via collateral and guarantee) and finally the small risks can be even accepted. These actions, i.e., avoidance, reduction, transformation and acceptance of risks are treatment part of risk management.

Implementation and evaluation: Once the risk management strategy and guidelines for the risk treatment have been defined, its implementation and evaluation should start. The implementation and evaluation is carried out by the senior management, staffs by using IT infrastructure and statistical models on both existing and new investment transactions. Frequently, effectiveness of risk management strategy must be evaluated in order to verify that whether the resulting risk taking remains in the line with the strategy and to apply corrections where necessary. Evaluation includes examining of risk drivers, evaluation of risk measurement process in the back testing procedure.

1.3 Principles of credit risk management

Even though bank failures and difficulties could have a number of different reasons, common cause of serious bank difficulties have been connected to weak credit risk standards for clients and borrowers, poor credit risk management for credit portfolio, inadequate awareness to changes in economic and other circumstances that drive to a deterioration in creditworthiness of counterparties. In order to provide general recommendations of sound credit risk management to bankers, practitioners and supervisors all over the world, Basel (we will discuss next section) formed key principles that banks and supervisors should take into account in every process of credit risk management and supervision.

The principles contains below four areas (BIS, 2000):

First one is *the* ***establishing of appropriate credit risk environment*** that is implemented through two steps of actions:

Credit risk policies and strategies of a bank must be developed, approved, reviewed periodically by board or senior management team. The strategy must include all possible scenarios and profitability the bank expects to achieve for incurring credit risks.

Executive management team must be responsible for implementation of credit risk strategies approved by board and develop procedures and rules for all processes of credit risk management at individual credit and portfolio level.

Banks must identify all credit risks inherent in all the products they offer and in the activities they are engaged in. Products or activities that are newly introduced by a bank should be reviewed and approved by bank senior management or appropriate committee before introduced and undertaken (BIS, 2000).

Next important area is *operating under clear and sound credit granting process*. It includes all activities starting from identification of target market, appropriate credit application screening and evaluation, goal and usage of financing, cash flow and ratio analysis, approval process, financing structure to repayment sources of counterparty. In addition to this, banks should have limits that are set for exposures to individual counterparties and borrowers or different types of economic sector such as consumption, construction or agricultural etc.

Third important are of key principles of credit risk management is establishing an appropriate credit administration, measurement and monitoring process. This includes continuous credit monitoring system, maintaining internal credit rating system that suits the bank's own characteristics, size, complexity, information system that enables the bank analyze credit portfolio and identify credit risk concentration and control credit quality at both individual loan and portfolio level.

Last is role of supervision for maintaining sound credit risk management system. Supervisors should require that banks to have effective system to identify, measure, monitor and control credit risk as part of an overall approach to risk management. Supervisors should conduct an independent evaluation of a bank's strategies, policies, procedures and practices related to the granting of credit and the ongoing management of the portfolio. Supervisors should consider setting prudential limits to restrict bank exposures to single borrowers or groups of connected counterparties.

1.4 Basel Accord and Credit risk management approaches

The Basel Accords refer to the banking supervision Accords (recommendations on banking laws and regulations)—Basel I and Basel II issued—by the Basel Committee on Banking Supervision (BCBS). The Committee consists of representatives from world major 20 economies. Recommendations and standards from the Committee don't have legal authority to enforce to any country, but most member countries as well as some other countries tend to implement the Committee's policies through national laws and regulations.

Initially main objectives of the Accords were: to require banks to maintain enough capital to absorb losses without causing systemic problems and, to create a level playing field internationally by establishing the framework that should be fair and consistent to banks in different countries.

1.4.1 Basel I

Basel I Accords were created to enhance the harmonization of regulatory and capital adequacy standards only within member states of the Basel Committee. General scope of the Basel I are described in academic literatures as follows: (e.g. (Balin, 2008) and (Adrian Blundell-Wignall, 2010)). Firstly, member states are regarded as developed economies by international institutions, and therefore, the standards set forth in Basel I are developed for the banks within such economies. Basel accord gives substantial leeway to state central banks, views domestic currency, debt as the most reliable and safe financial instruments, sees that government deposit insurance as risk-reduction, and uses a "maximum" level of risk to calculate its capital requirements that is only appropriate for developed economies, its implementation could create a false sense of security within an emerging economy's financial sector while creating new, less obvious risks for its banks. Secondly, the Accords are created for risks those are stemmed from bank loan book. It is not for reserve of capital to guard against risks such as instability in a national currency, changes in macroeconomic recessions and changes in interest rates.

The Accord is divided into four sections. The first pillar is *The Constitutions of Capital* describes capital types that are accounted as bank reserves and amounts of capital reserves bank must hold for each type. Capital reserve is divided two sections known as Tier I and Tier II[1] respectively. Second pillar of Basel I Accord, *Risk Weighting*, sets up a complete system to risk weights for a bank asset, e.g., bank loan book. Bank's balance sheet asset makes up five types of risk category and each of the asset groups is matched to a risk weight depending on its risk category. Third pillar, A Target Standard Ratio, consolidates first two pillars. Banks are required to meet minimum standard that 8% of bank's risk weighted assets must be covered by Tier I and Tier II capital reserves. In addition, Tier I capital must cover 4% of a bank's risk weighted assets. The ratio is known as "minimum adequacy" to protect against credit risk in international banks.

Criticism and shortcomings of the Basel I come from following sources. One vein of criticism focuses on its narrow scope compared with the goal of ensuring adequate financial stability in international financial system. The Accord deals with only credit risk and targets G-10 countries. There was lack of the other risks types (e.g. interest rate, operational, business) and financial infrastructure issues (e.g. accounting, legal framework) did not provide adequate incentives to encourage complementary improvements in banks' risk governance and measurement (Saunders & Linda, 2002).

The second group of criticism involves issues regarding risk categories and weightings. The use of only four broad risks weighting categories for capital charges can't distinguish different level of credit risk implanted in banking portfolio especially for complex institutions. Banks have

[1] Tier I capital (core equity) includes stock issues and disclosed reserves. Tier II capital includes perpetual securities, unrealized gains on investment securities, hybrid capital instruments, long term subordinated debt with maturity higher than 5 years. Total capital comprises the sum of Tier 1 and Tier 2 capital less any required deductions.

obtained tactics to avoid Basel I standards to put more risks on their assets than that was expected by the framers of Basel Accord. Through asset securitization, banks have been securitize their loans and able to lower their credit risk-based capital requirements without reducing the actual risk. Then, the gained money through this securitization can be added to a bank's asset reserves, allowing it to disburse even more risky loans. By doing this, banks, on paper, are perfectly protecting against credit risk, but in reality are taking on number of risk far greater than what Basel I intended.

Next source of criticisms relate to its application to emerging markets. Because of interconnection among world economy, even the Basel I was tailored to be applied to developed market economy, its application to developing economies under the pressure of the international business and policy communities started to generate foreseen and unforeseen distortions within the banking sectors of developing economies.

Firstly, in countries subject to high currency fluctuation and sovereign default risks, the Basel I accords actually made loanbooks riskier by encouraging the movement of both bank and sovereign debt holdings from OECD sources to higher-yielding domestic sources. Next, government deposit insurance, combined with lax regulation on what assets fall under Basel I's risk weightings, caused emerging market regulators to underestimate the credit default risks of a bank's assets. This created systematic defaults within emerging market banking sectors when it became obvious that all banks had taken on excessive risk and when it was revealed that the country's central bank had the capital on hand to bail out some of the banking sector (Balin, 2008).

In addition to the clear shortcomings of Basel I in emerging markets, several unforeseen effects of Basel I also made the accord less desirable for developing economies. The first unforeseen consequence of Basel I is a consequences of its risk-weights bank debt: because short-run non-OECD bank debt is risk-weighted at a lower relative riskiness than long-term debt, Basel I has enhanced investors to move from owning long-run emerging market bank debt to owning short-run developing market instruments. That has encouraged risk of "hot money" in emerging markets and created more volatile emerging market currency fluctuations. Moreover, the lack developments of capital markets in emerging markets make capital adequacy ratios less reliable in the economies. Because the prices of stock and debt possessed by a bank are often incorrectly valued on illiquid emerging market exchanges, the risk-weightings of such instruments and the inclusion of these instruments in the calculation of a bank's capital adequacy ratio causes emerging market banks to show incorrect capital adequacy positions (Balin, 2008). In response to these problems and drawbacks and banking crisis of 1990s, Basel committee decided to propose new, more complex capital adequacy accord.

1.4.2 BASEL II

The Basel Accord II named as "A Revised Framework on International Convergence of Capital" was expanded greatly in terms of scope, depth and technicalities. Basel II regulation introduces three pillar structure, under first pillar, *Minimum Capital Requirements*, an institution is expected to compute minimum capital requirements for three financial risks; credit, market and operational risk. For each of these risks, bank can choose one out of several methods with different level of sophistication, where more advanced methods requiring more investment from the bank's side and tends to lead to lower capital requirements. Second pillar emphasizes interaction between regulator and bank and bank's external supervisory processes as well as internal review. Regulators are given the authorities to supervise internal risk evaluation procedures and processes in a bank and change them to more appropriate risk management approaches in the case they seen unable to manage risks proposed in pillar I. On the other side, banks must improve continuously their assessment of risks by reflecting its specific risk situation and adequacy of capital.

Figure 1: Basel II Accord Structure

The first Pillar Minimum capital requirements	The second Pillar Supervisory review process	The third Pillar Market discipline
Credit risk Market risk Operational risk	Internal capital adequacy assessment process Review process by supervisory body	Disclosure requirements

Source: based on BCBS (2006) adjusted by author

Pillar III describes market discipline within a country's banking sector. Banks and financial institutions are required and recommended to present and disclosure its capital and risk taking positions that were only published for regulators before. General figures like the aggregate amounts of capital i.e., Tier 1 and Tier 2 held by a bank, risk-weighted capital adequacy ratios, reserve requirements for credit, market, and operational risk, and description and assumptions of the risk mitigation approaches of a bank are recommended for quarterly release to the general public under Basel II's standards.

After the financial crisis 2008, most of the drawbacks and problems of Basel II were considered as shortcomings arose from calculation of Minimum capital requirements. In particular, it is revealed that credit risk measurement methods, risk weightings and its assumptions of the models were major reason of the recession and world is still dealing with the consequences of the greatest financial crisis since the Great Depression. In next section of the paper we shortly visit to Pillar 1 and some drawbacks related to its approaches.

1.4.3 Minimum Capital Requirements under Basel II

Pillar I is the most important and great section that occupy above 90 percent of total pages of the Accord. Formally, Capital adequacy ratio defined as following:

$$\text{CAR}=\frac{\text{capital (tier 1+tier 2+tier 3)}}{\text{credit risk+market risk+operational risk}^{2}}\geq 8\% \qquad (1)$$

If CAR is large enough, then it means that capital reserve to back bank asset is enough to cover unexpected losses. The higher CAR is that the higher the amount of sources from bank's shareholders. On the other hand too high level of CAR is not good either. It means that the shareholder's resources are not used in the most efficient way and can't take advantages of leverage.

Risk-weighted assets (RWA) and capital adequacy ratio are defined as:

$$\mathrm{RW} = \sum_{i=1}^{n} (\mathrm{A_i W_i}) \qquad (2)$$

Where: A_i- nominal value of asset i, W_i- risk weight for an asset and n- number of assets

Credit risk: In Basel II framework, three approaches to compute risk weighted assets are proposed. The first is standardized approach relies on external ratings that are given by market based external agencies, e.g., Moody's, Standard and Poor's. The second and third approaches are the foundation and advanced internal ratings based (IRB) approaches those are more sophisticated and supervisory authorities decide which banks qualify for the approach.

Standardized Approach to Measuring Credit Risk: Under the approach banks are required to use ratings from external credit assessment institutions in order to define the weights needed to calculate risk weighted assets. National supervisors are responsible for recognizing the external assessment institutions in accordance with specific eligibility criteria (e.g. objectivity, independency, disclosure, methodologies) as well as for mapping their assessments to the available risk weights (BCBS, 2006).

Bank's assets are classified into a set of standardized asset classes and risk weight is applied to each class reflecting degree of credit risk. Off balance sheet exposures are for capital purposes

[2] Operational risk is introduced in Basel II accord

transformed to into assets through application of credit conversion factors. In order to obtain the minimum capital requirement for credit risk purposes, all credit exposures, those are known as exposure at default in each bucket, are summed up, weighted by the appropriate risk weights and then multiplied by the overall total credit requirement of 8 percent. The standardized approach takes credit risk mitigation into account by adjusting the transactions EAD to reflect collateral, credit derivatives, guarantees and offsetting on balance sheet netting.

Internal Ratings-Based Approach (IRB): According to the approach each bank is required to establish an internal ratings model to classify the credit risk exposure of each activity on and off balance sheet. There are two versions of IRB approach: the foundation and the advanced IRB approaches.

In the foundation approach, banks, with the approval of regulators, can develop systems to model their own PD estimates and apply supervisory estimates for other risk components.

For more sophisticated banks are encouraged to move from the foundation to the advanced. The IRB approach requires banks to specify the probability of default (PD) for each individual credit, its loss-given-default (LGD), and the expected exposure at default (EED). This requires highly-complex modelling and aggregation, and offers banks with the necessary expertise the possibility of deriving more risk-sensitive weights.

*Operational risk: M*arket and credit risk are considered as financial risk that are caused by counterparty's financial behavior (default) and change on market value of underlying assets while operational risk is more connected with internal business processes and systems. Since 1990, operational risk management issues have been important in financial industry due to increased usage of information technology and programming which have direct effects for banks to expose number of external and internal frauds, errors and system failures those are caused by human or system itself. Until development of Basel II framework it was difficult to find generally accepted definitions about operational risk. The earliest definition was the following: *everything is operational risk, which is not under credit or market risk categories* (Homolya, 2007). BIS started to develop definition of operational risk from 2001 and the Risk Management

Group of the Basel Committee published special document for operational risk. Later in 2004, operational risk is described with Basel II Accord and definitive framework accepted by the industry is described for regulatory and supervision purposes. BIS defines operational risk*: as "the risk of loss resulting from in adequate or failed internal processes, people and systems or from external events"* (BCBS, 2006). The definition is rather broad and BIS and other literatures classify the definition following four risk categories (BCBS, 2006) and (Sironi & Resty, 2007):

People: it refers to losses originated from events such as human errors, frauds, abuse of internal procedures and rules and etc,

Systems: Those factors contain the events related to information system, and technology External and internal events such as hardware and/or software failures, computer hacking or viruses, and telecommunications failures refer to the risk. Technology based developments of financial instruments make the sector pay attention to this type of risks.

Processes: It refers to losses that are stemmed from inadequate internal processes and procedures. For instance: violation of information system security, work place safety rules, taxation error, transaction and settlement errors.

External events: The events are caused by external factors which affect bank profitability adversely and are not under control of bank management team. Examples could be unfavorable changes in political and legal environment, failures of suppliers or partners, criminal acts such as theft, vandalism, robbery, or terrorism, and natural events such as fire, earthquake and other natural disasters.

From the above mentioned definition and categorization we could say that in contrast to market and credit risk it is more occasional consequences from bank's fundamental business activities. That is why the operational risk is not avoidable and connected to bank business inherently. Another important difference of the risk is that increased exposure of operational risk is not reason of incremental income. The relationship between risk and return does not work for the risk. While in the case of financial risk higher risk is associated to higher expected return, that is not the case for operational risk.

To define capital reserves to guard against this risk, banks can opt one of the three methods purposed by Basel II accord: As purposed in the *Basic Indicator Approach* banks must hold capital reserve equal to fifteen percent of the average gross income of past three years.

Under the *Standardized Approach,* bank is divided different business line and units to define capital must be held for each business unit. Capital against operational risk is calculated by multiplying their gross operating income by a purposed percents by specific risk factor that is defined differently for each business line.

Third, more sophisticated one method is Advanced Measurement Approach. The method allows banks to develop their own models for operational risk management and minimum capital requirements. Like credit risk Advanced IRB approach the approach is subject to regulators approval. Basel provides three basic methods banks to model their internal models:

- internal measurement approach
- loss distribution approach
- scorecard approach.

Market risk: Market risk means the risk of changes in the market value of an instrument or portfolio of financial instruments, connected with unexpected changes in market conditions (stock prices, interest rates, exchange rates, and volatility of these variables); it therefore includes risks on currency, bond and stock positions, as well as on all other financial assets and liabilities traded by a bank (Sironi & Resty, 2007). There are five main categories of market risk: exchange rate, interest rate, commodity, equity risk and volatility risk.

Basel Accord attempts to quantify market risk. For fixed income assets, Value at risk approach recommended with the IRB approach and Advanced ORB approach. Banks can develop their own calculations to determine the reserve that is required to protect against interest rate and volatility risk.

There are two another approaches under Basel II for the banks that are not possible to use VAR: for interest rate risk of fixed income asset, banks must hold capital equal to risk weightings provided by Accord to guard against movements in interest rate. The risk weightings are given to assets depending on its maturity and fall from 0 to 12.5% of an assets value. In order to protect volatility risk of fixed income asset, Basel II suggests risk weighting attached with credit risk ratings associated to the underlying assets. To calculate total capital required to back market risk for fixed income asset, amount of each fixed asset is multiplied by assigned risk weighting and summed alongside all other fixed income asset.

Basel II defines another type of methods for other market assets-stocks, commodity, currencies: Simplified approach, Scenario analysis and Internal Model approach.

CHAPTER2. Credit risk measurement approaches

As we have discussed previous section of the paper, credit risk and its measurement is crucial for a bank business activities because the risk is inherently linked to significant section of a bank's asset cake. That is why the credit risk is on the centre of global financial industry and driving academicians and practitioners to develop a number of credit risk management techniques.

While banks and institutions in some part of the world are struggling with implementing and distinguishing most suitable and reliable ones from such a sophisticated approaches because of its complexity and technicality, another group of the organizations have been taking the advantages of choosing from the possible approaches that allow them to decrease required capital to protect against credit risk and increase profitability. For that reason, the paper's main objective is to examine most popular risk measurement methods.

Credit risk measurement models are classified into traditional and modern approaches. *Traditional approaches* to credit risk measurement have aim to define probability of default (PD) based on historical accounting data. However, the traditional approaches pay no attention to downgrades and upgrades in counterparty's creditworthiness which is consideration of market models and ignore company's equity structure, information on equity market. In the chapter, we review three traditional models used to estimate PD: (1) expert systems, including artificial neural networks; (2) rating systems; and (3) credit scoring models.

Modern approaches base on current market data of debt and/or equity to estimate a market measure of PD and are divided into two categories:

Structural Models: Predict the likelihood of default occurring over a given time horizon based on market data and an economic explanation of the default process (e.g. KMV, Risk Metrics)

Reduced Form Models: Use market information about credit spreads to extract default probabilities - they measure PD but give no explanation (e.g. Kamakura, KPMG)

Moreover, banks are increasingly measuring and managing credit risk at both the portfolio level and the transaction level. This has occurred for a number of reasons. First, banks realize that traditional classifications of good and bad loans are not sufficient to properly manage their credit risk because all credits could potentially default under a particular extraordinary economic scenario (C.Wilson, 1998). Second, possible errors in selecting and pricing individual loans are decreasing, but diversification and timing impacts on banks credit risk is increasing. Bank management needs more proactive risk measures for credit exposures after the loan has been originated. Stand alone risk models attempt to assess a borrower's credibility at transaction level while portfolio credit risk models focus on description of magnitude expected and unexpected loss in portfolio level. Considering this general introduction, we organize this chapter in following way: in section 2.1, traditional models for estimating PD and its main pros and cons will be depicted. Further, modern credit risk management models will be examined. Last part of the chapter is devoted for discussion about Value at Risk approach.

2.1 Traditional Approaches to Credit Risk Measurement

2.1.1 Expert systems

It is the oldest method for estimation of credit risk. To define credit default probability and make a credit decision, expert system bases on individual expert's subjective assessment, experience and risk weights assigned by experts to the key factors. The most popularly used expert system is known as "Five C's". The C's refer to:

(1) Character of borrower – includes analysis of historical financial performance, loan history and reputation for counterparty. Empirically it has been proved that duration of business activity is a proxy for business reputation more precisely willingness of repayment.

(2) Capital – deep analysis on equity including equity composition, owners' structure, leverage equity based ratio analysis.

(3) Capacity – this section of analysis investigate repayment ability based on earnings of a company. Amount of financing and its repayment must be matched to the earning stream of a company.

(4) Collateral – Investigation of assets that are pledged by client. In the case of default bank has a right to claim the asset, market price and its trend is important for the group of analysis.

(5) Condition - The state of the business cycle; an important element in determining credit risk exposure, especially for cycle-dependent industries.

Basically, the five C's are analyzed to define a creditworthiness of a particular client, weight them in a subjective way and reach an estimated probability of default. Expert's assessment of the factors is subjective and difficult to standardize, that could result inconsistent measurement in some case (Saunders & Linda, 2002).

In 1981 economist Stiglitz and Weiss proved that there is a high nonlinear relationship between the level of interest rates and expected return on a loan because of two phenomena: adverse selection and risk shifting (Saunders & Linda, 2002). Thus, besides the five "C's", interest rate is a factor that should be taken into account by an expert. Even the expert system is still used in practices, there have been two obvious disadvantages: it does not answer precisely on question that how we should choose common factors used to analyze different types of borrowers and what are the appropriate weights should be assigned to each risk factors.

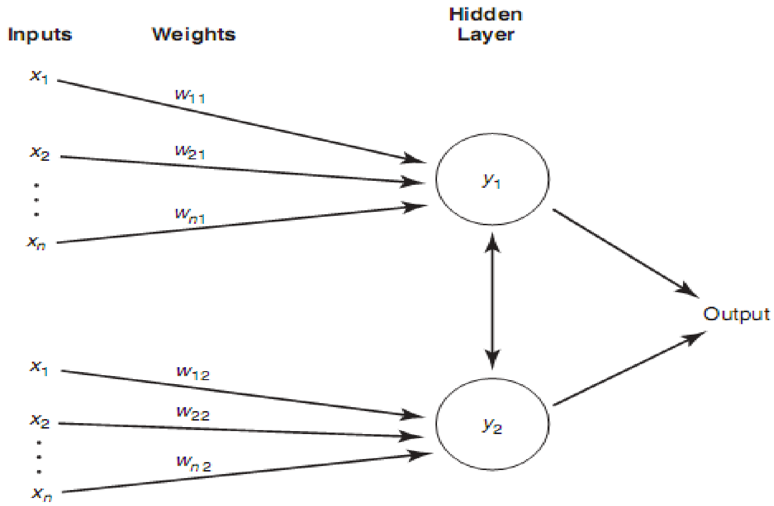
Artificial neural networks

Neural networks are inspired by the way biological nervous systems, such as the brain,process information. They typically consist of many nodes that send a certain output if they receive a specific input from the other nodes to which they are connected (Bernd Engelmann, 2006).

This approach is extension of expert system and developed to overcome above mentioned drawbacks of expert system. General idea of the artificial neural networks is that developed software is used to evaluate expert system more consistently and objectively.

The inputs for system are: 1) inputs, 2) weights and 3) hidden units. Two-layer hidden neural system is shown on the Figure 2.

Figure 2: Neural network



Its works by simulating human learning process in a way that the system learns the nature of the relationship between input data and outcome score and 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 main advantages of neural network is the ability to update itself. Every time neural network estimates the credit risk of a possible loan, it automatically updates its weight scheme (Saunders & Linda, 2002). In addition to this, in short time horizon its prediction power is high. Kim and Scott (1991) use the system to predict bankruptcy using 190 companys' data. The system predicts very well for a short time period (87%) and performance is worsened dramatically for a long period showing 47% for four year time period prior to bankruptcy.

Major disadvantage of such estimation is the lack of transparency: it is impossible to interpret the internal structure of the system and intermediate steps can not be checked. Thus checking consistency of output from the system is almost impossible (Saunders & Linda, 2002).

2.1.2 Credit scoring models

Nowadays, credit scoring models are a widely used computer based system that is mostly employed by major financial institutions to quantify the risk factors of retail and consumer lending counterparties. Initially, the credit scoring models are employed to estimation of consumer credit and lately started to be used for private individual borrowers with increase of the credit demand for small and medium sized business loans. The reason for this increased use of the scoring methods is that the methods are relatively cheap, bases on historical data and simple compared to modern approaches. Some research (e.g., Mester (1997)) revealed widespread use of credit scoring models showing that 97 percent of the banks use credit scoring to approve credit card application, whereas 70 percent of the banks use credit scoring in their small business lending.

In order to estimate default probability credit scoring models use statistical and mathematical methods. Main goal is to differentiate good and bad customers based on variables which have most statistical explanatory power to predict PD. General idea behind the models is quite similar to expert system, comprising two steps: pre-identification of key input factors that determine PD e.g., company's financial ratios, financial history and economical indicators and combining and weighting factors using a weight that mirrors its influences in forecasting PD. Result from the models could be interpreted as default probability and, in other case the score and cut-off point are used to distinguish potential borrowers into good or bad groups.

In terms of data needed to assess credit risk by credit scoring models, it varies depending on credit types. For consumer and private customer lending, customer and his family information, income and employment status, repayment history and outstanding loan account numbers and loan amount are used as main risk factors. Data inputs for medium and small business lending, cash flow based analysis and ratios are considered likely candidates to assess financial strength and industrial, operating environment and management capabilities are considered as candidates for non financial risk factors.

We will study three methodological forms of credit scoring models. 1) Linear regression model 2) Logit and probit models 3) Multiple discriminant analysis.

Linear regression model: The linear regression model is based on a linear regression analysis, and makes use of a number of accounting variables try to predict the probability of default. Main steps to model credit risk as following:

Sample selection: it is important to form sample by large number of companies could represent whole population. The sample is divided by two groups indicated by a binary state variable y, which takes value 0 if a particular borrower is non default or 1 for others.

Choice of explanatory variables: As mentioned previous section the explanatory variables are usually economic and financial factors such as leverage, probability, liquidity and turnover etc.

Estimation of regression coefficient: Using the dependent and independent variables, we run below regression with ordinary least squares (OLS) to estimate coefficients.

$$Z_i = \Sigma\beta_j \; x_{i,j} + \varepsilon_i \qquad (3)$$

Estimated probability of default: Then take these estimated β_js and multiply with the observed X_{ij} for a prospective borrower, we can derive an expected value of Z_i for the prospective borrower. That value can be interpreted as the expected probability of default.

$$E(Zi) = 1 - Pi. \qquad (4)$$

This problem has a big disadvantage with bounding dependent variable, probability of default, between 0 and 1. As a result, the outcome of the model can’t be interpreted as PD but, it could be used for comparison between borrowers showing that higher value of Z associated with higher default risk.

Advantages and disadvantages of the model are (Bernd Engelmann, 2006):

OLS is most common and easy econometric method. As model is linear computation and its results are easily understandable. Because of heteroscedasticity (i.e., the variance of error term is not constant for all i), the estimated coefficients are inefficient and standard error of estimated coefficients is biased.

Logit and probit models: Second group of statistical method are logit and probit econometric techniques. Using binomial logit and probit estimation methods with dummy dependent variables allow to avoid above mentioned unboundedness of linear probability model. The differences between logit and probit arises from distributional assumption about residuals. If we assume that residuals are normal distributed then estimation method will be probit and if assumed logistic distribution then it will be logit.

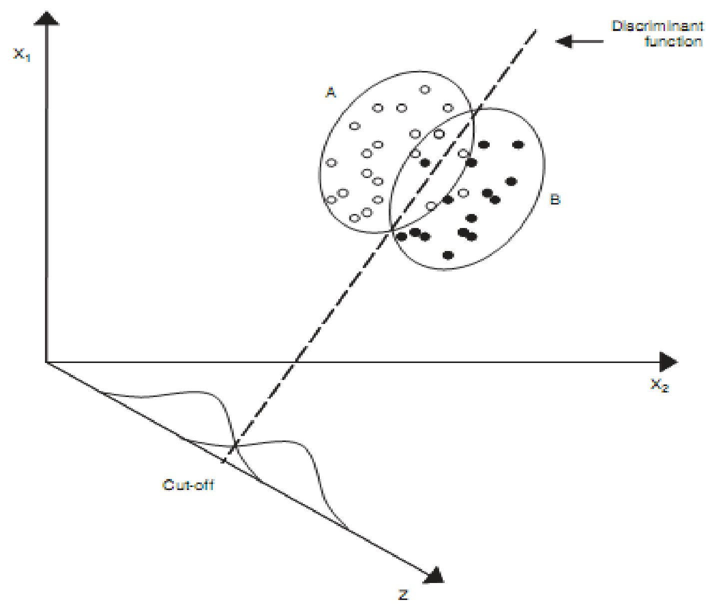
Advantage of the logit method is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis does. It incorporates nonlinear effects, and uses the logistic cumulative function in predicting a bankruptcy (Bhatia, 2006). In ordinary least square (OLS) analysis, the error variance (residuals) is assumed to be normally distributed. For the dichotomous distribution, which is predicted by Logit model outcome is prediction of binary outcome, variance is assumed to be logistically distributed.

The logit and Probit models usually yield almost same results and researchers tend to use with most familiar of them. Probit finds the measure of the goodness of an applicant, but whether the applicant is actually good or bad depends on whether the score is greater or less than a cut-off level (Bernd Engelmann, 2006).

A major shortcoming for those types of model is that interpretation of estimation coefficients are not straightforward while they have some following advantages: the methods are theoretically sound, the result will be interpreted as PD directly and significance of model and individual coefficients are possible to be tested.

Discriminant analysis model: This method initially was studied by Fisher in 1936. Using identified variables (economic and financial ratios calculated from financial statements) model attempt to discriminate between good and bad prospective borrowers based on a discriminant function. Figure 3 illustrates simplified discriminant analysis with two variables, x_1 and x_2. Scores by combining the reliable (A) and unhealthy (B) companies' two variables are shown on z axis.

Figure 3: Graphic Illustration of Discriminant Analysis



The score generated on z axis is constructed as linier combination of the independent variables. In general, assuming n independent variables, score is produced by below function:

$$z=\sum_{j=1}^{n} \mu j\ xj \qquad (5)$$

The coefficient μ_j of this linear combination are chosen so as to obtain a z score which discriminate as clearly as possible between abnormal and healthy companies. In other words, core question is whether the groups are significantly different from each other with respect to the mean value to the mean value of a given variables.

A famous example of this type of method is Altman's z-score model for listed US companies analyzed in 1968 by Edward Altman. In practice, most models are variants of Altman's z-score model (Saunders & Linda, 2002). The discriminant model by E.I. Altman:

$$z = 1.2X_1 + 1.4\,X_2 + 3.3\,X_3 + 0.6\,X_4 + 1.0\,X_5 \qquad (7)$$

Where z = an overall measure of the default risk

X_1 = Working Capital/Total Assets

X_2 = Retained Earnings/Total Assets

X_3 = Earnings before Interest & Taxes/Total Assets

X_4 = Market Value of Equity/Book Value of Long-term Debt

X_5 = Sales/Total Assets

According to Altman's credit scoring model cut-off point is set up 1.81 defined that mean value z for a sample of good companies and the mean value of z for bad companies those have become default. It means:

$Z > 1.81 \Rightarrow$ Low default risk class

$Z < 1.81 \Rightarrow$ High default risk class

Like in linear regression model the absolute result of Z score can not be explained as PD directly but it can be used to rank particular customers by their z scores.

As underlying theory behind the discriminant and linear regression analysis is common then, the benefits and drawbacks of discriminant analysis are similar to those of the regression model (Bernd Engelmann, 2006):

First of all, this is a widely known method with estimation algorithms that are easily available. Once the coefficients are estimated, the scores can be calculated in a straightforward way with a linear function. Since the characteristics x_i are assumed to be realizations of random variables, the statistical tests for the significance of the model and the coefficients rely on the assumption of multivariate normality. This is, however, unrealistic for the variables typically used in rating models as for example financial ratios from the balance-sheet.

2.2 Modern approaches to credit risk measurement

While traditional models to credit risk measurement models have been demonstrated to perform quite well in many different counties and over different time periods, there have been number of critics. First of all, the traditional models heavily rely on accounting data which is inflexible and updated infrequently. The assumption that there is linear relationship between dependent variable and independence variables is unrealistic whereas the path to bankruptcy may be highly nonlinear. At third, credit scoring models are weakly linked to underlying theoretical model. In response to these drawbacks and shortcomings capital market based approaches started to be evolved since 1970s (Saunders & Linda, 2002).

On the other side, developments of international capital market have led developments in mathematical asset pricing models. The development leads security prices- those are mirror of all available information as well as of the expectations of investors- being as major input in prediction of other market variables and estimation of the likelihood of default (Sironi & Resty, 2007).

Modern credit risk measurement models could be divided two groups: an options-theoretic structural approach initiated by Merton (1974) and a reduced form approach pioneered by Jarrow and Turnbull (1995), Jarrow, Lando, and Turnbull (1997), and Duffie and Singleton (1998, 1999). These two schools of thought offer differing methodologies to accomplish the central task of all credit risk measurement models estimation of default probabilities (Saunders & Linda, 2002).

2.2.1 Structural models based on stock prices

Merton (1974) used option pricing theory, developed by Black and Scholes (1973), to value risky loans. Nowadays, initial idea is broadly extended in many directions in order to eliminate certain unrealistic assumptions and enhance its practical utility.

General intuition behind the Merton model was: a company will default when the value of its asset becomes lower than value of its liabilities. In other words, a company invests borrowed money into varies of projects and the owners of the company have incentive to repay its loan in the case company's market value of asset is exceeded loan value. If market value of the company's asset is lower than loan amount after one year period then the owner has incentive to default and transfer its remaining asset to lender. The behavior makes the loan payoff to the lender similar to writing put options on assets of the borrowing company (Saunders & Linda, 2002).

There are two important benefits to Merton model: It shows effectively what variables drive a company to default. The variables are the ratio of debt to assets which is proxy for financial risk and volatility of company's asset returns, which depends on expected operating cash flow of a company, therefore represents company's business risk. Second benefit is calculation of PD is done in an objective, clear and formal sophisticated way. Despite these benefits, there are number of shortcomings, especially those are arises from practical implications of the model (Sironi & Resty, 2007).

- At first, the problems stem from assumption of a single zero coupon liability and standard normal distribution of asset return. In practice, of course, companies have complex financial liabilities with different maturities and variety of periodical interest payments.
- Next problem is that some inputs to model aren't observable from stock market directly e.g., market value of asset and volatility of asset's return.

  A third limitation comes from assumption of constant risk free interest rates.

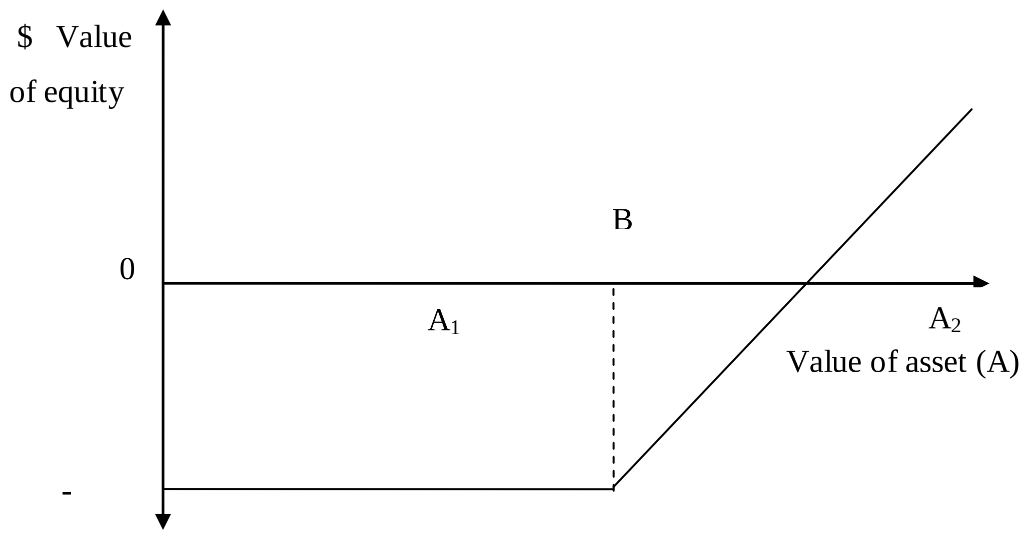
  And last one is that model only focuses on default risk not migration risk, i.e., risk is due to deterioration in issuer's credit rating.

KMV, California based Corporation acquired by Moody's lately, extended Merton's initial model by dealing with most of the above listed problems and the model is known as KMV-Merton. The model has two fundamental assumptions:

- Total value of firm follows geometric Brownian motion.
- Company has just one single liability i.e., zero coupon bond with maturity T.

Based on these assumptions, model considers equity of a levered company as a call option on a company's asset with a strike price equal amount to debt repayment. In other words, at maturity, company's shareholders can exercise the option to purchase company's asset in case market value of assets is higher than its debt value or accept the default otherwise. Thus, company's probability of default can be expressed as the probability that the market value of the company's assets will be less than the repayment value of the loan at maturity.

Figure 4: Equity of a levered company as a call option on assets in the KMV model



Source: (Saunders & Linda, 2002)

In order to define the probability, it applies simple equation that market value of firm asset is sum of **market value of the equity** and **market value of debt**. By subtracting the face value of company's debt from market value of firm and then dividing this difference by estimate of the volatility of firm, a score called distance to default can be described. Then the distance to default is substituted into cumulative density function to calculate the probability that value of company is less than the face value of debt. In case a company is publicly listed, we can get market value of a company from stock market while reliable data on market value of deft is generally unobservable.

KMV-Merton model estimates **value of debt** by employing Merton bond pricing model and considers value of equity as function of the total value of firm described by Black-Scholes-Merton (Eq.8) formula. By put-call parity, the value of the company's debt is equal to the value of a risk-free discount bond minus the value of a put option written on the firm with strike price equal to the face value of debt and a time-to maturity of T (Shumway, 2005).

$$E = VN(d_1) - e^{-rt}FN(d_2)) \qquad (8)$$

where E is themarket value of the firm's equity, F is the face value of the firm's debt, r is the instantaneous risk-free rate, N(·) is the cumulative standard normal distribution function, d_1 is given by

$$d_1 = \frac{\ln\left(\frac{V}{F}\right)+\left(r+0.5\delta_v^2\right)T}{\delta_v\sqrt{T}} \qquad (9)$$

and d_2 is calculated as $d_2 = d_1 - \delta_v\sqrt{T}$ (Shumway, 2005).

Based on Black Scholes formula and above mentioned assumptions, volatility of the company is defined by following equation. Estimation of volatility of the company's equity is derived from historical stock returns information or option valotality data.

$$\sigma_E = \left(\frac{V}{E}\right)N(d_1)\sigma_V \qquad (10)$$

After determining v and δ_v from the equations (8) and (9), determination of PD in KMV-Merton model is based on following equation (Eq.11).

$$PD_{kmv} = N\left[-\left(\frac{\ln\left(\frac{V}{F}+\left(r+0.5\sigma_v^2\right)*T\right.}{\sigma_v\sqrt{T}}\right)\right]\text{=N(-DD)} \qquad (11)$$

As illustrated in Allen, Saunders (2002), (Sironi & Resty, 2007) and others, the model has number of advantages and disadvantages: 1) it is directly applicable any public traded companies, 2) it is forward looking because the determinant of the PD is derived from stock market data and 3) the model has strong theoretical foundation because it is a structural model based on the modern theory of corporate finance. Main disadvantage is normality assumption of asset return, which is a statistic that depicts observed default frequency as a function of distance to default. Second, it is not suitable to be used for unlisted companies because the market value and volatility of equity are unavailable.

2.2.2 Reduced form model

Whereas structural models employ information embedded in equity prices to predict default risk, reduced form models use debt price to reach the goal. In contrast to structural models hypothesis, above discussed, a company will go to bankrupt at the point where company's asset value is below the value of debt, reduced form models set a flexible assumptions allowing more factors that affect the probability of default (Jens HilscHer, August 2008). More specifically, reduced form models the default event is exogenous but risk premium is observable in deft prices and yields (i.e., observed yield on risky debt is can be decomposed into a risk free rate plus a risk premium). The higher yields demanded by investors for risky bonds reflect market expectations as to likelihood of issuer default. These spreads, therefore, represent summary of all available information on the factors (both systematic and specific) that influence PD.

The models work in risk neutral market which means that all investors are assumed to accept the same expected return as promised by the risk free asset. Considering such behavior, the asset price could be valued as discounting future cash flows in the asset by the risk free rate. The relationship is utilized to describe back out risk neutral probability of default.

One of the approaches that represent reduced form models is KPMG's loan analysis proprietary model used popularly for both default prediction and loan valuation. Basically, it decomposes of the yield into credit risk free rate and credit risk premium. 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. 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.

2.2.3 Value at risk and Credit metrics

Value at risk (VAR) methodology developed as a risk measurement from mid of 1990s. The concept started to measure market risk exposures more accurately by taking into account its volatility, maturity, and correlations among assets. The similar logic to market risk VAR estimation is adopted for credit risk on the bank loan portfolio is referred as Credit Value at Risk. VAR concept is favored for three major reasons, which are providing a complete view of portfolio risk, measuring economic capital, and assigning a fungible value to risk (Bessis). In general, VAR can be defined as the worst loss that might be expected from holding a security or portfolio over a given period of time given a specified level of profitability which is known as the confidence level. This implies that the loss higher than value at risk could be suffered only with small probabilities. Based on the simplified assumption and calculations, VAR consolidate all risks in a portfolio and report understandable, suitable for users.(Pearson, 1996)

There are three basic approaches applied to measure Value at Risk. VAR can be measured by portfolio historical data, Monte Carlo simulation and using variance covariance matrix across risk.

Historical simulation: It requires small number of simplified assumptions on market data and statistical features and considered relatively easy to implement. Historical approach creates hypothetical time series of returns on portfolio by processing the portfolio trough real historical data of portfolio and calculating change that could occur at each period of time. However, there is a couple of shortcomings of historical simulation, and first of all is that it imposes a restriction on the estimation assuming asset returns are independent and identically-distributed (iid) which is not the case. From empirical evidence, it is known that asset returns are clearly not independent as they exhibit certain patterns such as volatility clustering. Second restriction relates to time. Historical simulation, it applies equal weight to all returns of the whole period and this is inconsistent with the nature where there is diminishing predictability of data that are further away from the present. These two shortcomings leads economists and financial experts to further develop other non-parametric, semi-parametric and parametric models.

Variance covariance approach: This method assumes that asset returns are normally distributed. In other words, it requires that we estimate only two factors - an expected (or average) return and a standard deviation - which allow us to plot a normal distribution curve. The idea behind the variance-covariance is similar to the ideas behind the historical method - except that we use the familiar curve instead of actual data. The advantage of the normal curve is that we automatically know where the worst 5% and 1% lie on the curve.

Monte Carlo simulation: This method has number of similar aspects to historical simulation. Main difference of the simulation is that it allows one to choose a statistical distribution that is believed to represent or approximate possible changes in the market factors. After choosing the possible distribution function, random generator will be used for delivering number of hypothetical values of market values. 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.

In terms of general result of the three approaches, they produce almost same outputs as given the identical assumptions. As the first two methods are basically rely on market data, which at some cases (e.g. not publicly traded securities or lack of information) could be challenging for performing necessary calculation. As a solution for his shortcoming, J.P. Morgan (together with Bank of America, KMV and others) developed Credit metrics, a framework for VaR calculation, main features of which are described below.

Credit metrics

Credit metrics assumes that credit risk doesn't occur due to not only default of a borrower also it is driven by downgrading of obligor's rating. However, for a loan or bond, the market price and its volatility are not available. Therefore, Credit metrics models theoretical price and volatility for a single loan or bond using following four variables: (l) available data on a borrower's credit rating, (2) the probability of that rating changing over the next year (the rating transition matrix), (3) recovery rates on defaulted loans, and (4) yield spreads in the bond market.

Modeling begins with specification of a rating system and calculation of a transition matrix, which represents the average annual frequencies of migration among credit classes. Banks can use a commercial rating system and its transition matrix constructed by Moody's or Standard & Poor's, or own internal rating system.

Value of a loan under different risk rating is calculated by discounting future cash flows from the loan (yearly interest rate and principal amount) at a discount rate which is sum of risk free rates on a risk free asset and annual credit spread on a particular rating class of each year. From the new values of each probable grades and expected value of probability weighted loan and variance the value are derived.

According to (Saunders & Linda, 2002), credit metrics produces two types of VAR based on normal distribution of loan values and based on actual distribution of loan values. Under the normal distribution, the expected value at the end of the time horizon is calculated as sum of the each possible loan value times its transition probability over the time horizon. The volatility of loan value can be found from the distribution of the loan values and VAR can be calculated based on standard deviation and normal distribution parameters. However, the calculated VAR is likely underestimated because of the normal distribution assumption. Indeed, credit risk distribution demonstrates non symmetric and long downside tail of the distribution. VAR estimates based on actual distributions can be derived from the distribution of a loan values using linear interpolation for desired significance level of VAR. Correlations among defaults are inferred from correlations between asset prices.

Chapter 3.Credit risk in Mongolian banking sector

Mongolia is one of the most sparsely populated countries in the world with a population of 2.6 million and an area of 1.5641 million km^2. Average population density is 1.54 persons per 1 km^2. In terms of land area, it is 18^{th} largest country in the world. Until 1991, Mongolian economy was based on a centrally planned model[3] that had been adopted more than 70 years. After communist regimes collapsed in east European countries, Mongolia saw its Democratic revolution in early 1990 which led the country to the transition market economy.

In terms of economy structure, agricultural sector accounts for about 20 percent of real GDP and herding and livestock are dominating in this sector by creating 89 percent of total agricultural production . Besides of agricultural sector, mining is important to the economy. In 2001, mining sector constituted 9.5% of GDP, whereas in 2009 the sector is earning 30% of GDP and accounting for 50% of industrial sector output (BOM, 2009). In addition, mining sector income makes up 80 percent of export income. As described in Mongolian mining sector report (TD The Market Publishers, Ltd), the growth of Mongolian mining has only just begun. The biggest is the gold/copper mine at Oyu Tolgoi which is considered to have the potential to be one of the world's richest mine deposit with the reserves that will last 60 years. The other is the 6.4 bn tonnes of coking coal deposits at Tavan Tolgoi, which while smaller in financial potential is still attracting the attention of the biggest corporate players in the mining world.

[3] Centrally planned economies assume that the market does not work in the best interest of the people, and that in order for social and national objectives to be met a central authority needs to make decisions. The state can set prices for goods and determine how much is produced, and can focus labor and resources on industries and projects without having to wait for private investment capital.(http://www.investopedia.com/terms/c/centrally-planned-economy.asp)

Table 1: Key Macroeconomic indicators

Key Indicators	2005	2006	2007	2008	2009
Population (000)	2,562	2,595	2,635	2,684	2,737
Population growth (%)	1.2	1.2	1.5	1.8	1.9
GDP (mill. USD)	2,067	3,189	3,931	4,837	4,197
GDP growth (%)	7.3	8.6	10.2	8.9	-1.6
GDP per capita(USD)	894	1,237	1,490	1,819	1,532
Inflation (%)	11.6	6	18	22	4
Exchange rate (MNT/US$)	1,221	1,165	1,170	1,268	1,443
Export (mill. USD)	1,054	1,543	1,948	2,535	1,903
Trade Balance (mill. USD)	-95	107	-114	-710	-229
% of population below minimum living standard	n/a	n/a	n/a	36.1	n/a

Source: ((NSO), 2008)

3.1 Historical performance of credit risk

As common in other transition countries, financial sector has been dominated by banking sector. Before 1990, Mongolia had one tier banking system and central bank of Mongolia was fulfilling central and commercial banking role simultaneously. In 1991, Mongolian banking system reorganized into two tier banking system, with Bank of Mongolia (BOM) acting as central bank implementing monetary policy and ensuring banking sector stability and security while other commercial banks providing commercial services to economy.

At the early stage of the transition to market economy, Mongolian banking sector has suffered by three large crises in 1994, 1996 and 1999, due to weak regulation and supervision framework, less experience with the modern commercial banking practices, poor management ability and lack of professional human resources. Through 1990-2000, overall 30 commercial banks were set up and only half of them survived. Out of 14 banks' bankruptcies, eight failures were caused by credit risk with high non-performing loans (NPLs). Others were caused by low equity capital ending up insolvency and operational risk because the staff and managers at the banks were involved in insider lending and fraud (Enkhhuyag, 2004).

NPLs were accumulated mainly in two ways: ***ineffective and unprofitable state owned enterprises*** were directly reflected into NPLs of banks' balance sheet. Secondly, ***poor credit policy, management and control and lack of market discipline*** caused systematic banking crises of 1990s.

In order to eliminate insolvency of the banking sector BoM and government had taken urgent measures and made banking sector restructuring during the banking crises time and the cost of restructuring was reaching 2%, 7.8% of GDP in 1992, 1996 respectively. Furthermore, in 1999 once again three large banks which held 22 percent of total banking asset became illiquid and insolvent. The cost of these banking crises to budget estimated at 0.6% of GDP in 2001 (Shagdar, 2007).

Thanks to the Mongolian banking sector restructuring and privatization, monetary policies implemented over the past years, gradual improvement was observed in banking and financial service sector after experienced a number of impediments. At the end of 2003, there were 16 commercial bank and 88 nonfinancial institutions in Mongolia, with total of 635 offices, about 75.3% of which served in rural areas.

4.2 Recent development of credit exposure and its risk

As mentioned above, banks are playing dominant role in Mongolian financial sector. As of the end 2008, 95 % of total asset in financial sector is constituted by banking sector with 14 commercial banks and only 5% percent from nonbanking sector, including non financial institutions, saving and credit cooperatives (SCCs) and insurance and security companies.

The ratio of market capitalization to GDP is one of the indicators that show capital market development. According to Mongolian Financial Regulatory Commission's report the ratio is 8.4 percent in 2008 and capital market is substantially underdeveloped compared to developed economies such as Germany, Japan, South Korea, Great Britain and USA, where the ratios fall between 52.6-160.2 percent. In case of Russia, China, Kazakhstan, Kyrgyzstan those are between 41.6-89.7 percent (BOM and Financial regulatory commission[4], 2008).

Market structure: At the end of 2009, number of commercial banks operating in Mongolia stands at 15 including one branch of foreign bank, with the total asset of 70% of the country's GDP and 1080 branches serving 2.6 million populations. Out of 14 banks, ten banks are foreign investment participated, three are pure domestic and one is state owned, State bank. In 2003 state owned two banks, the Trade and development bank (TDB)[5] and the Agricultural bank (KHAN bank)[6] were acquired by foreign investors through international tenders. The State bank is established in 2010 based on healthy section of Zoos bank's asset. The bank became insolvent due to violation of loan disbursement limit to a single borrower, resulting in poor loan quality and unprofitability. Moreover, as a result of a merger between Mongol Shuudan and Savings bank, just Savings bank remained actively on the market. Table 2 shows number of banks acting in and its structure.

[4] Financial regulatory commission responsible for regulation and supervision financial institutions, including credit unions and nondeposit-taking lenders, capital markets, and insurance companies

[5] The Trade and development bank was sold to Global Investment and Development joint consortium of Banco Lugano Commerciale of Switzerland and Gerald motors Inc, of the US, lately IFC and ADB owned 9.08 and 9.08% of equity respectively, since 2003 ING Advisory has been providing management advice and technical assistance to TDB. (Annual repost TDB,2005)

[6] KHAN bank is the largest bank, with 469 branches in Mongolian every administrative district. Sawada Holdings of Japan is the largest shareholder with a 52.9% interest. Other investors include the Tavan Bogd Group of Mongolia (35.3%) and Development Alternatives, Inc. (DAI) of the US and IFC.

Table 2: Banks number and ownership

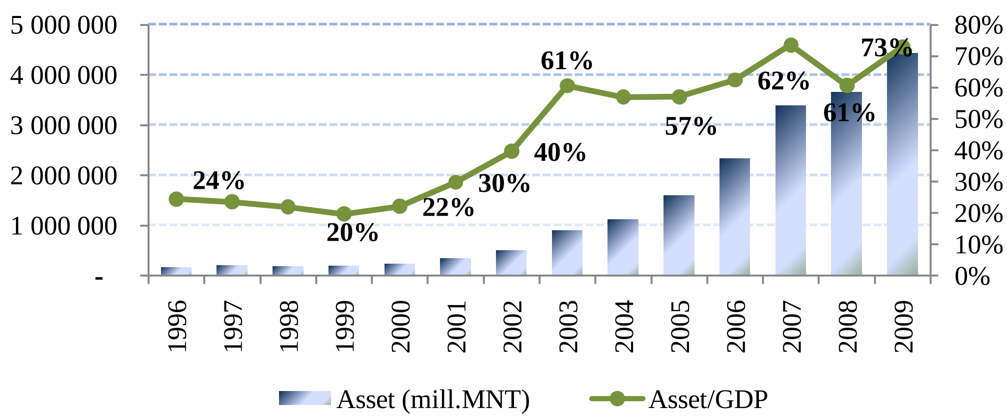
Years	2000	2004	2008	2010
State owned	2	1	0	1
Private	10	16	16	13
Domestic	10	10	6	3
Foreign		6	10	10
Total banks	12	17	16	14

Source: (BOM, 2009)

Aggregated balance sheet: Total banking sector asset hits 4.4 trillion MNT (3.06 bill.USD) and accounts for 73% of GDP. Between 2000-2007 total bank assets growth averaged at 39%, amounting to around 60% percent of the country's GDP. In 2008-2009 the total asset grew by only 19% as a result of steady appreciation of the USD dollar and reserve increase of banks, as desired by the central bank after the failure of the two commercial banks at the end of 2009.

The banking sector has been characterized through relatively high concentration by three largest banks (Khan, TDB, Golomt) holding more around 70 percent of banking asset. (Figure 5)

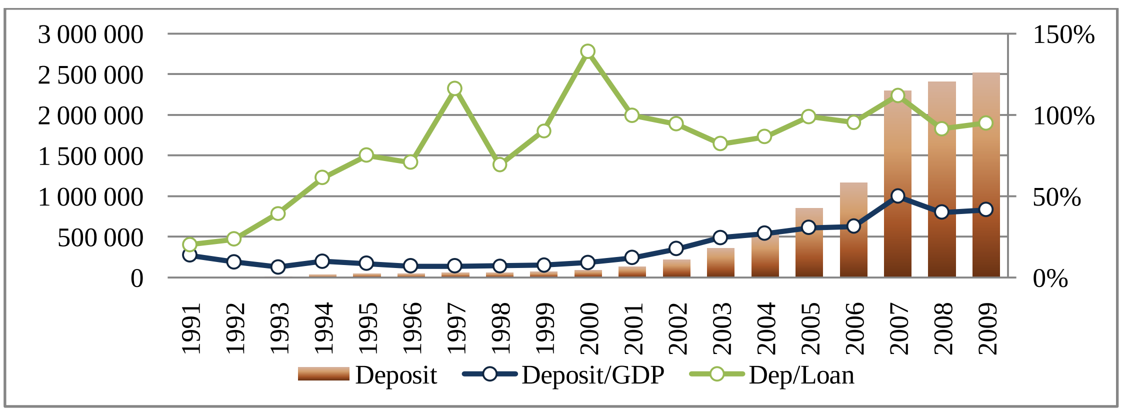
Figure 5: Time series of asset and ratio of asset to GDP



Source: (BOM, 2009)

Aggregate liability: Increasing public confidence on banking sector was revealed growth of domestic deposit, which was growing 59% annually in 2001-2007. This high growth rate suddenly started decreasing in 2008 and banking sector deposit went out of banks by impact global economic crises; however, as a result of government guarantee on banks deposit, the deposit outflow slowed down and deposit amount remained same as amount of pre crises. One of the traditional measure of banking sector depth and development is deposit to GDP ratio. It shows gradual increase until 50 percent in 2009. Domestic deposit to loan ratio in banking sector is presently close to 1 which reflects that banks funding primarily supported by domestic depositors rather than dependence on foreign funding. However, the trend decreased slightly in 2008 and 2009 shows further potential vulnerability. (See table 6)

Figure 6: Time series of deposit and Ratio of deposit to GDP and loan to GDP



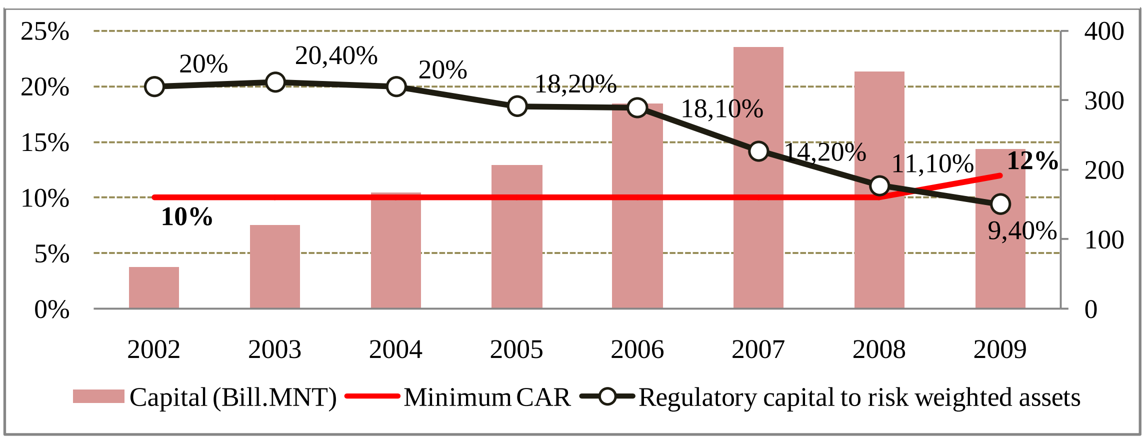
Source: BOM Annual reports and author calculation

The domestic deposit interest rate is relatively high in Mongolia compared to other developing countries. It is around 13% in Mongolia as compared to for example around 8% in Azerbaijin, 6.5% in Vietnam and 2% in Cambodia (Ianchovichina & Gooptu, 2008). This is mainly due to competition pressures in recent years that drove the deposit rate higher as well on the lending rate. Accordingly, spread between the loan charge and deposit rate, the interest rate spread is again higher in Mongolia compared to those countries. This can be explained by the fact that banks prefer to increase the loan rate instead of assessing the associated credit risk through sophisticated risk management techniques.

Capital adequacy: Banks in Mongolia have to maintain a minimum Capital Adequacy Ratio (CAR) of not less than 12 percent of their risk weighted asset (with at least 6 percent in core capital). In 2009, banking sector capital declined by 58 percent and amount of MNT 178.1 bill compared to the end of the 2008. The capital adequacy ratio declined mainly due to Zoos and Anod banks' losses, which incurred because of raising NPLs and heighten market risk. If Anod and Zoos bank are excluded from the statistic, capital adequacy ratio could stand at 14% which is decreased by 1.3 percentage point from 2008. Nevertheless, average banking sector CAR is still above international threshold level 8 percent.

While CAR is decreasing in banking sector, BOM revised its regulation of prudential ratios and made decision to increase CAR to 12% in 2009. Objective of this measurement was that to help deal with pro-cyclicality in banking sector and enhance resilience of both individual banks and the banking sector as a whole. According to BOM report, small banks are not able to meet capital adequacy ratio and in order to meet the requirement and it is needed to add MNT 64.1 billion additional capital into a whole banking system which is equal to 1% of GDP.

Figure 7: Capital adequacy ratio for Mongolian banking sector



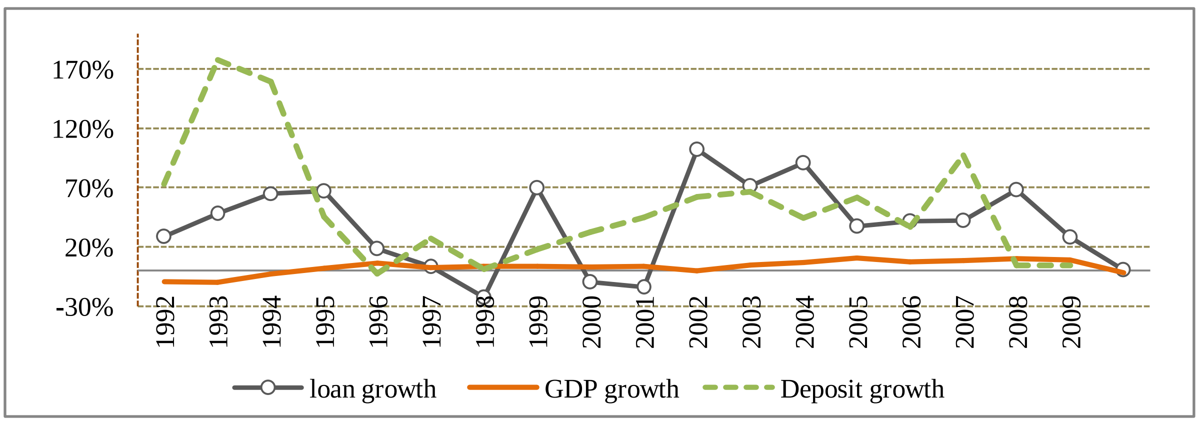
Source: (BOM, 2009)

3.2 Lending practices and credit risk

As Mongolian economy grows, bank lending was widened substantially over the past few years. According to BOM reports, until 2000, the total banking sector loan portfolio was around 50 billion which was about 8 percent of GDP. Rapid loan expansion started from 2000 and the total outstanding grew 81.5 percent each year until 2005, then by 42 percent (rising to

1.05 billion) in 2006, 68.1 percent (to $1.76 billion) in 2007 (Figure 8). Meantime average annual growth of broad money was 36.5 percent. The speed of loan extension outperformed other macroeconomics indicators such as GDP growth and deposit growth.

Figure 8: Development of loan, deposit and GDP growth (annual)

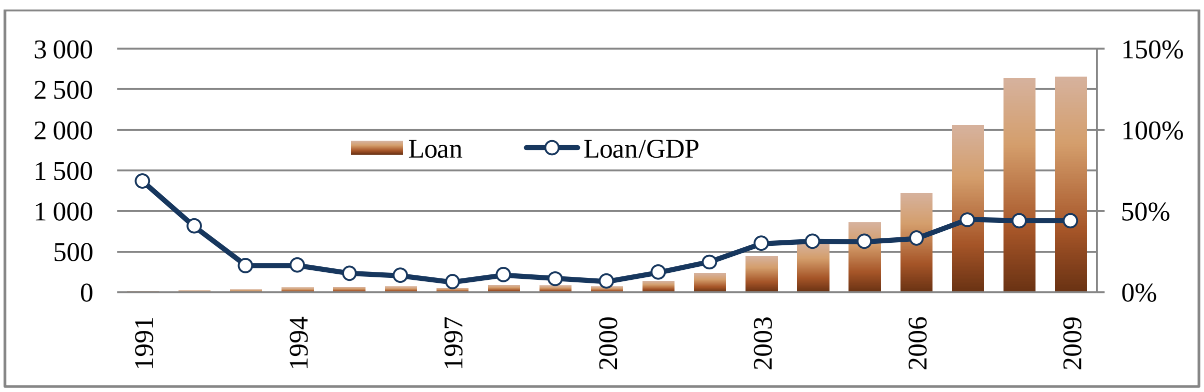


Source: (BOM, 2009), ((NSO), 2008)

Until 2006, the growth characterized by increased loans issued to individuals (from 9% of total loan in 2000 to 35% at the end of 2005) and decreased loans to private sector (from 72.3% in 2000 to 57.8% in 2005) which nevertheless remain high. Moreover, by sector non-industry sector has driven the loans to private entities, raised from 52% in 2000 to 57% in 2005.

During the 2008, global economic crisis affected most of domestic market through decrease of main export good prices (e.g. in 2009 copper price decrease reached 60% in international commodity market), reversal of foreign direct investment and increase of main import products' prices. Due to all these impacts, domestic economy started slowdown and banking sector lending activities started to be stagnant. In 2008, total outstanding loan growth was 28 percent in 2008 and in 2009 just keep its amount as previous year. As the end of 2009, banking sector total outstanding loan realized as 2.6 trillion MNT (1.7 billion USD).

Figure 9: Total banking sector loan portfolio and Loan to GDP ratio

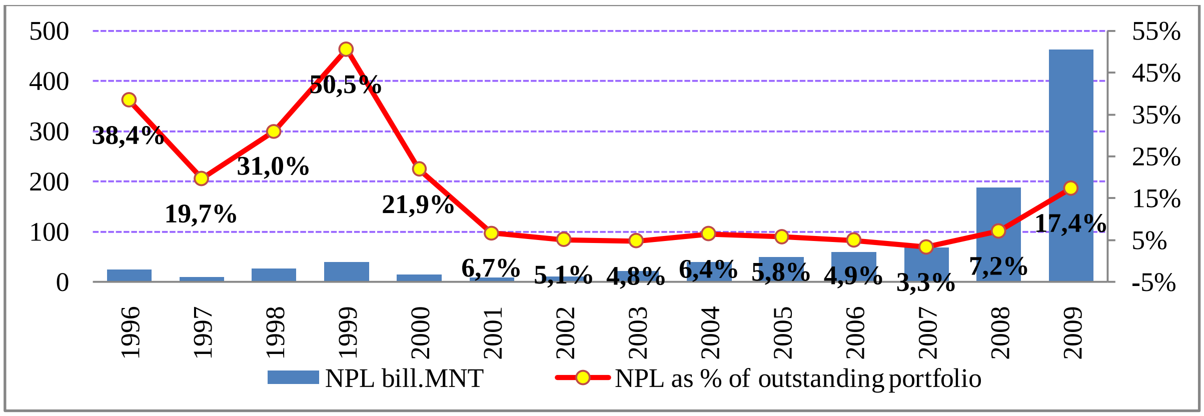


Source: (BOM, 2009), ((NSO), 2008)

Consequently, credit risk in banking sector shows dramatic growth. Until 2007, NPL to total loan ratio was decreasing gradually and standing around 5 percent; however, the ratio shot up to 7.2 percent in 2008 and 17.2 percent in 2009.

The NPL portfolio doubled in 2008 and 2009 compared to previous year (Figure 10). Excluding the two failed banks, NPLs and loans with principal in arrears as a percent of total loans outstanding amounted to 11.1 percent as of end-August, down from a peak of 19.7 percent in September 2009.

Figure 10: NPL and NPL as % of outstanding portfolio



Source: BOM annual reports

Figure 10 shows that amount of NPL had been gradually increased over the last 10 years in absolute term. Therefore, it is questionable whether the decreased ratio of NPLs to total portfolio is as a result of effective credit risk management or rapid credit growth. During last 10 years average loan growth was 54 percent and average NPLs growth was 58 percent and the decrease of the ratio is mostly explained by rapid credit expansion.

On the other hand, if one looks at loan provisioning change and dynamic of NPL to total loan portfolio ratio, loan portfolio quality is not improved overall, because there is not any considerable decrease in provisioning and loan loss provisioning ratio increased last 3 years. The trend exhibits that further likelihood of bad influence on profitability.

Figure 11: Loan provision to Total loan portfolio ratio and loan provision growth

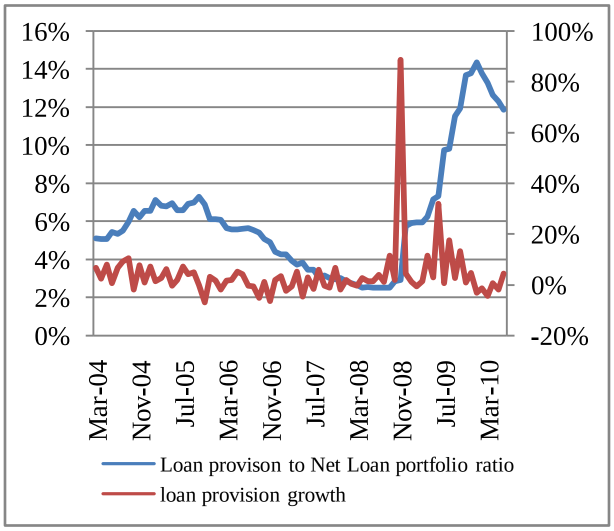
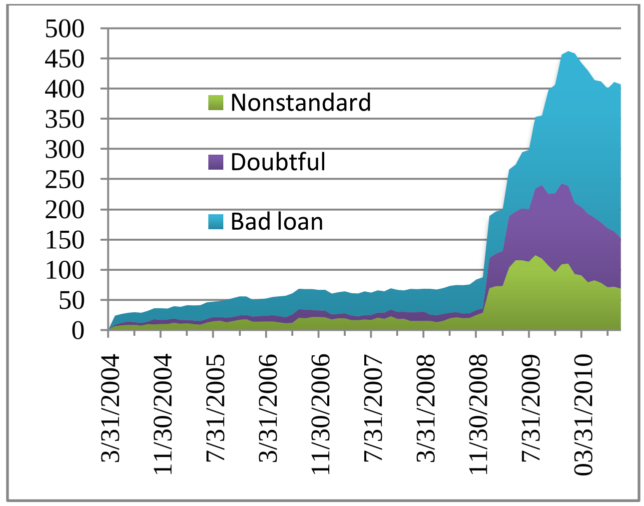


Figure 12: Structure of NPLs (Billion MNT)



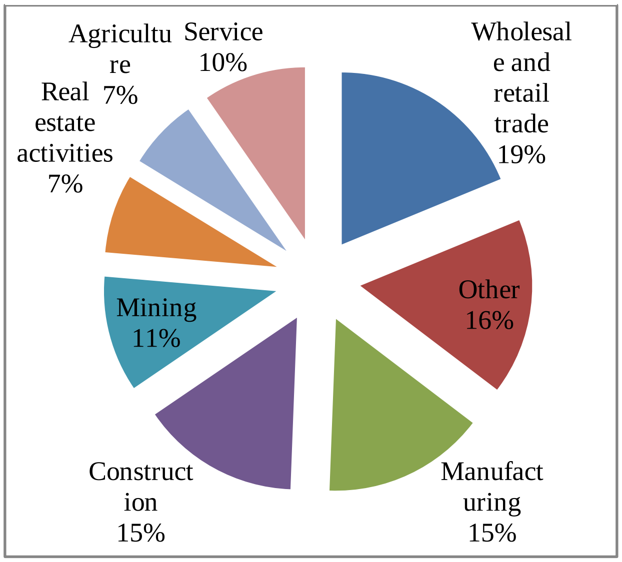
Source: Based on BOM report

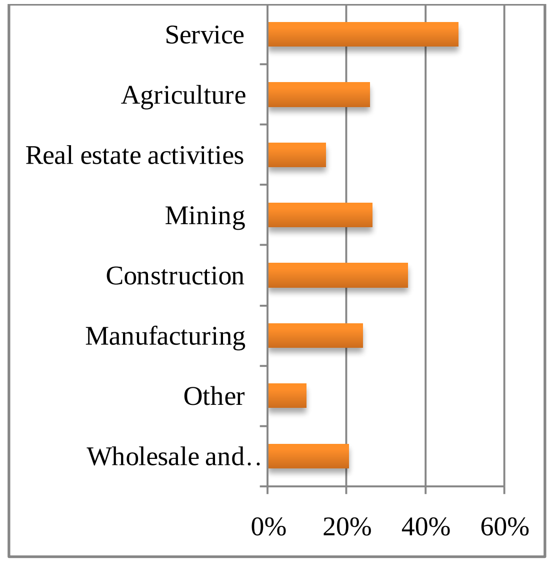
Nonperforming loan structure: Portion of bad loan in NPL is increased dramatically to 50 percent with amount of MNT 223 billion in 2009 (figure 12). While loan in arrears are decreased to 85 billion from MNT 173 billion a year ago, the NPLs are still stable and unpaid. However, the percent of NPLs in total loans also varies across commercial banks.

As reported in ((IMF), 2008) the four largest banks having NPL to total loan ratios are significantly smaller than those for the five smallest banks. Due to the small size of the less strongly performing banks, the risks are less of a systemic nature and more to the BOM's reputation as a supervisor.

In terms of sector performance, credit quality deterioration is more observed in construction, agriculture and transportation sector characterized by high percent of NPLs. Moreover, while private sector ratio of NPL loan to its sector total portfolio is 25% percent, loan to individuals NPLs percentage is 9 % which is mostly two times lower than ratio of NPL to total loan for entire banking sector.

Figure 13: Credit portfolio structure and NPLs by sector as of Dec 2009





Portfolio concentration: In terms of portfolio diversification, correspondence with Mongolian economy structure, banking sector loan portfolio mainly constituted by construction, retail and whole sale, manufacturing and mining sectors. Mortgage lending does not represent a significant share of overall loan portfolios. Similar to asset structure loan portfolio is concentrated on 3 large banks they make up 63 percent of loan portfolio.

As of August 2008, private sector loans accounted for only 56.9 percent, or $1.35 billion, and 49 percent of these loans, valued at $666 million, were in foreign currency. Loans to individuals (which are often used for productive purposes, especially within the informal sector) accounted for 40.9 percent of all private sector lending, with $542 million targeted at the microfinance sector. Approximately 10.9 percent of this amount, or $59 million, had been disbursed in U.S. dollars.

Loan maturity: Most loans, roughly 80% of all loans extended are with very short term maturity, mostly less than 5 year while credits with 5 years or more maturity make up only 5% of total loans. 36 percent of total loan portfolio is up to 1 year. There are demands of long term loan to investment, but Mongolian banking sector deposit structure is mainly dominated by time deposit with short term and high interest rate. On the other hand this is due to the seasonality of business activities of Mongolian economic sector. For example, mining and agricultural sector is active only a half of the year due to long and harsh winters. Banks try to set the loan repayment term as short as possible as not to raise disincentive to repay loan.

Chapter 4.Credit risk measurement: Application and results

As stated in previous chapter, it is clear that credit risk management capacity and effectiveness is crucial issue for both individual commercial bank and whole sector in Mongolia where banking sector makes up 95% of total financial system.

In practical section of the research, we concentrate on an analysis of credit risk modeling for Small and Medium Enterprises' (SME) exposures in Mongolia. Adoption and implementation of modern sophisticated credit risk measurement methods are real challenge for Mongolian bankers due to lack of experience with ideal commercial banking, under development of financial sector, short history of commercial lending and absence of historical official and commercial business bureau. Secondly, as demonstrated in previous section, dramatic increase in loan portfolio that is characterized by loans to SME and retail clients started from 2006 and competition pressures require bankers to employ more professionalized credit risk measurement approaches in order to decrease loan interest rate as optimized credit risk measurement methodology. Further, this rapid growth of private sector credit could create key challenge in future. In 2010 and 2011, Mongolian banks recorded 61.5% and 80.0% increases in retail and SME loan portfolio, respectively. On the other hand, if we compare ratio of retail and SME bank loan exposures to GDP in some countries in 2009, it is expected that the amount of loans to retail clientele will continue to increase, as there is a lot of space for expansion in the portfolio in Mongolia (See table 3). That is why it is important to examine appropriate default risk model for SME exposures in Mongolian context.

Table 3: Private sector loan portfolio vs GDP for some selected countries

India	China	Thailand	Mongolia	EU & Taipei
6%	15%	24%	26%	52%

In chapter 2, we introduce number of statistical and latest methods for building as well as estimating internal rating models of a financial institutions' credit risk. With the development of many new techniques and tools, the choice of the suitable and reliable model is becoming more and more complex. As demonstrated in literatures, one should consider some factors to choose particular class of models over another. First of all model performance is the most important one. And then, data availability and quality is crucial. Most of the models perform excellent in theoretical framework, but don't work in practice mostly due to missing values and data. Considering the facts, firstly we will reexamine Atman-Z score model and will define how reliable it is in emerging market economy. Further we will employ logistic regression econometric methodology to the sample SME's data in Mongolia and will compare model performance to Altman Z csore predictions. Logistic regression model is most popular model in practice as well as in the academic literatures for some reasons. Firstly, the output of the model can be interpreted as PD directly, and secondly, it is easy to check if dependence between potential explanatory variables and PD is economically meaningful. Since 1980s, logistic regression started to be preferred by practitioners and replaced the linear discriminant analysis gradually.

4.1 Data set and processing

In this section, we will briefly introduce our dataset. The SME's data used in the study is taken from a Mongolian Commercial bank that operates in micro financial sector. As the bank is social-oriented, development bank, most of loan portfolio is constituted by individual client's loan portfolio while only 25% percent of loan portfolio is disbursed to SMEs. Original data, set which was supplied from the bank consisted of 245 individual companies to which a loan granted spanning 2006-2008. We kept out certain type of borrowers from the sample, i.e., some public and big companies that don't present typical Mongolian SMEs. Rather we left small and micro firms with average turnover 120 million MNT (66.4 thousand EUR).

According to Mongolian Small and Medium enterprise's law, SME is defined by annual turnover, which is determined by calculating the income that the enterprise earned during the year and number of staff who are work full time with lobar contract. In the definition SMEs fall into three major categories namely, micro, small and medium-sized as in EU. As definition of micro-sized firms it must be with turnover less than 250 million MNT and with lower than nine staff, all SMEs included in the sample fall within the micro- sized categories. We excluded some companies because of some obvious mistakes, such as negative sales amount, unbalanced balance sheet and missing information of some section in financial statements. All companies' financial statements are stated in thousand Mongolian tukrigs (MNT) and prepared very briefly. (see enclosed excel file)

Finally, we selected 32 companies as a sample for analysis out of the total population(245 SMEs). 12 of them were representative of bankrupted companies (the companies as declared and listed as bankrupted by Mongolian Tax Authority and did not make any payment to their bank loan since 2008), the rest companies perform in normal way.

Defining independent variables and calculation of financial ratios

The usage of the credit risk models and choice of the risk factors are motivated by both practical and theoretical consideration. Moreover, economical and statistical significant risk factors measure default risk more sensitively and reflect borrowers' financial situation and, therefore, warn default risk efficiently (Bhatia, 2006). Once financial data is ready to analysis, potential independent variables have to be selected. We attempt to calculate all possible financial ratios based on very briefly stated financial statements as it enables us to standardize the available information. For example, the ratio return on asset presents a comparison of profitability of firms of different size. Moreover, the financial ratios or candidates for independent variables will be calculated as it represents most important credit risk factors, i.e. leverage, liquidity, productivity, turnover activity, firm size and profitability. The calculation of financial ratios and its explanation were mainly based on "Corporate finance" by (Jaffe, 2005) and "Investment Analysis and Portfolio Management" by (Brown, 2007).

Table 4: Financial ratios and descriptive statistics

Financial ratios		Credit risk factor	Hypot hesis	Mean	Standard deviation	Min	Max
Total Liability/Total asset	TL/TA	Leverage	+	0,65	0,48	0,07	2,21
Total Liability/Tangible asset	TL/Tan A	Leverage	+	0,29	0,34	0,00	1,53
Equity/total asset	E/TA	Leverage	-	0,36	0,51	- 1,21	1,15
Bank debt/total asset	BD/TA	Leverage	+	0,20	0,28	-	1,47
Short term debt/ total asset	STD/TA	Liquidity	+	0,55	0,58	0,07	2,37
Current asset/current liability	CA/CL	Liquidity	-	2,56	2,51	0,32	12,20
Account receiveable/ net sales	R/NS	Liquidity	+	0,39	0,32	0,08	1,43
Current asset/TA	CA/TA	Liquidity	-	0,69	0,20	0,10	0,96
Cash/ TA	C/TA	Liquidity	-	0,27	0,21	0,01	0,82
Current asset/Net sales	CA/TS	Liquidity	-/+	0,68	0,43	0,19	2,21
Cash/Current liabilities	C/CL	Liquidity	-	1,27	2,12	0,02	10,90
WC/Current liabilities	WC/CL	Liquidity	-	1,56	2,51	- 0,68	11,20
EBIT/Total asset=ROA	EBIT/TA	Profitability	-	- 0,13	0,32	- 1,46	0,14
Net income/Total revenue	NI/TR	Profitability	-	- 0,20	0,45	- 1,91	0,11
EBIT/Equity=ROE	EBIT/E	Profitability	-	- 2,41	10,19	- 55,12	2,46
WC/TA	WC/TA	Liquidity	-	0,20	0,49	- 1,39	0,84
RE/TA	RE/TA	Profitability	-	- 0,20	0,40	- 1,60	0,10
MVE/TL	MVE/TL	Leverage	-	0,36	0,51	- 1,21	1,15
Sales/TA	S/TA	Turnover	-	1,38	0,83	0,22	4,32

In the above table, all examined ratios that are analyzed through the research are displayed with credit risk factors. Also, the table includes descriptive statistics for the variables. In the column hypothesis, we depict the expected dependence between calculated ratios and default probability, where + indicates an increase in the ratio leads to an increase in default probability and – symbolizes a decrease in the default probability given an increase in the ratio.

Leverage: Most effective as well as common factor for predicting default risk is leverage. Basically, leveraging is a way to use funds whereby most of the money is raised by borrowing rather than use of equity capital. Ratios that are under the leverage category indicate how much the business relies on debt financing and are used to measure the ability to meet its financial obligation. Therefore, those ratios, except equity to total asset should have a positive relationship with default. As can be seen in the table we calculated five accounting ratios in the leverage group.

Liquidity: This group of ratio measures a firm's ability to pay off its short term debt obligation. The ratios are calculated by comparing firm's liquid asset against its short term liabilities. Generally, the greater the coverage of liquid assets to short term liabilities, the more likely is that a business will be able to pay debt as they become due to while still funding ongoing operations. There are two common liquidity ratios: the current ratio, calculated by dividing total current assets by total liabilities; and the quick ratio, calculated by deducting inventories from current assets and then dividing by current liabilities. In the 4 table we provide nine ratios for this group of ratios.

Profitability: The measurement is expressed in various accounting ratios that either measure profit relative to assets or relative to sales. A firm's profitability is positively related to its default event. Four ratios, return on asset, net profit ratio, return on equity and retained earnings total asset are calculated to be included in the analysis.

Turnover: The ratios indicate efficient usage of available capital. High sales to total asset ratio is precondition to earn high return with relatively low investment. It has a positive effect on the liquidity of a firm and reduces default probability.

4.2 Altman Z-score Model and results

This section will be devoted to computing Altman Z-score for companies in the selected sample. Here we will check the results of chosen model and compare them to real number of bankrupted firms.

The attempts to identify most powerful accounting indicators that could help to predict bankruptcies started in 1930s as studied by Fisher, known Fisher's linear discriminant analysis (Rym, 2005). Further development in the field was performed by A. Altman, a famous economist and professor in New York University. Using different 22 accounting ratios of manufacturing firms for twenty years time span, Altman (1968) evaluated the prediction power of variables which signals corporate failure. The professor tested different combinations of the variables as well as joint significance of different models and individual significance of each variable separately. Finally, he defined a best performing model, which includes five factors for bankruptcy prediction and set the base for other researchers to examine the validity of multivariate models. The model is presented as follows:

Z-Score = $1.2x_1 + 1.4\ x_2 + 3.3\ x_3 + 0.6\ x_4 + 1.0\ x_5$

where:

Z= Cumulative Z-score
X_1 = Working Capital/Total Assets
X_2 = Retained Earnings/Total Assets
X_3 = Earnings Before Interest & Tax/Total Assets
X_4 = Market Value of Equity/Total Liabilities
X_5 = Sales/Total Assets

Estimating the chosen sample firms through the model, Altman concluded that it had 72 percent accuracy in evaluating corporate failures two years prior to that event occurs.

Further we will discuss importance and meaning of each individual variable of the model and display results for the sample SMEs that is explained in section 2 in detail.

<u>Working Capital/Total Assets:</u> This ratio is proven to be most relevant one because it measures net liquid asset of a firm relative to the total capitalization. A firm with negative working capital is likely to experience problems in meeting its short-term obligations because there simply are not enough current assets to cover those obligations. By contrast, a firm with significantly positive working capital rarely has trouble paying its bills.

<u>Retained Earnings/Total Assets:</u> The ratio measures the amount of reinvested earnings or losses, which reflects the extent of the company's leverage. Companies with low RE/TA are financing

capital expenditure through borrowings rather than through retained earnings. Companies with high RE/TA suggest a history of profitability and the ability to stand up to a bad year of losses. On the other hand, it differentiates companies by their age: younger company have lower ratio due to they have not accumulated sufficient revenue, so older companies have ratio will be somewhat higher. It makes sense because more experienced companies more likely not to be default from historical and business cycle perspective. As retained earning are not depicted in our brief balance sheet information, we take net profit of the year instead of retained earning.

Earnings Before Interest and Tax/Total Assets: This is a version profitability measurement, an effective way of assessing a firm's ability to squeeze profits from its assets before factors like interest and tax are deducted.

Market Value of Equity/Total Liabilities: This is a ratio that shows –degree on devaluation of the company’s assets with respect to the total book value of liabilities. This ratio is quite innovative as added a market value aspect to the model. In other words, a durable market capitalization can be interpreted as the market's confidence in the company's solid financial position.

Sales/Total Assets: This tells investors how well management handles competition and how efficiently the firm uses assets to generate sales. Failure to grow market share translates into a low or falling the ratio.

Rule for classification of companies is that companies with lower Z-scores are more likely to be bankrupted. Companies with scores above 3 are unlikely to enter bankruptcy. A z-score value between 1.81 and 2.99 is called in gray area firm, which is concluded that uncertain about credit risk exposure. Score below than 1.81 indicates that the company is about to go bankrupt or bankrupted.

Results: We show here our findings of Altman Z-score model calculated in our data set for two years. Further in order to validate the model we will examine percentage of cases that is predicted correctly through the model.

# of companies	Years	
	2007	2008
Z-score> 3	3	5
1.81<Z-score<2.99	10	3
Z-score<1.81	19	24
All	32	42
Real # of bankrupted companies	12	12
Average of Z scores	0.59	1.12

Questions under our consideration are: at first, we will concern with whether the Altman-Z score model was successful in classification of the companies which went to bankrupt in 2009 and secondly, whether it succeeded in estimating the companies that performed well during the year. In order to illustrate this, we will demonstrate type 1 and 2 errors for the given results. In our case type 1 error is expressed as percentage of firms that are classified that not bankrupted, but actually they have bankrupted. In contrary, type 2 error will gives us percentage of firms that had predicted as bankrupted, but they did not go bankruptcy in reality. Following table shows the result:

Table 5: Altman Z-scores prediction statistics

	Altman Z-scores prediction statistics							
	Bankrupted companies				Non-Bankrupted companies			
Years	All	Correctly classified	Type 1 error	% correct	All	Correctly classified	Type 2 error	% correct
2007	12	9	3	75%	30	15	15	50%
2008	12	11	1	92%	20	12	8	60%

According to our calculation, the model could identify almost all (92 percent) bankrupted companies prior one year to bankruptcy, in 2008. If we make the calculation using the firms' data of 2007, (which means two years in advance) the model successfully marked 75% of defaulted companies as bankruptcy candidates.

Similar to number of empirical researches which have a goal to test prediction accuracy of Altman Z-score model, result of the our empirical study shows decreasing trend in percentage of correct prediction as increase the time span between the bankruptcy occurred and z-scores are calculated. For example, original study of (Altman, Sep.,1968) says that the model is extremely accurate in predicting bankruptcy in 94 percent for USA manufacturing for one year prior and decreased the accuracy until 36 percent for five years prior to bankruptcy.

In addition to this, he developed four variable-Altman Z-score prediction model for listed companies in China that is a huge proxy for emerging markets for financial year 2007. General conclusion was that identified four ratios those are statistically powerful to predict firm’s failure were very similar to Altman’s original model and back substation test was indicating that predictive accuracy of the established model reached 100 percent when classifying test samples. (Edward I. Altman, November 2007)

4.3 Logistic regression model and its result

We described basic characteristics of credit scoring models such as linear probability model, logit and probit model. From the approaches employed in development of probability model for dummy dependent variable we use logit model to estimate and build a model that will predict probability of default for our selected sample data. In this section, we will explain in a bit detail about technical aspects of the logit model and then explore result and tests.

The logit model is based on the cumulative logistic probability function. In this function, the probability that y_i=1 is given by following equation (Studenmund, 2009). :

$$p(y = 1) = \frac{e^s}{1 + e^s}$$

Where: $s = \alpha + \beta_i x_i + u_i$; i= 1…n where n is number of observation, x_i is vector of explanatory variables for the i^{th} observation, β is vector of parameters that are obtained by maximum likelihood estimation, and u_i is disturbance term of i^{th} observation. The dependent variable y has the following properties:

$$y_i \begin{cases} = 1 \; if \; y_i > 0 \\ = 0 \; if \; y_i \leq 0 \end{cases} \text{ with } y_i = 1 \; if \; borrower \; i \; default, otherwise \; y_i = 0$$

Pre- selection of independent variables

We have specified our independent variable candidates in subsection 4.1. In order to build robust[7] model variable selection and preparation is important factor (Anderson, 2007). Thus one of the important conditions that should be considered before estimation of a model through any statistical software is checking correlation between independent variables. Besides having significant power of prediction, in many instances, a lot of characteristics will be highly correlated with each other, especially those are calculated using same, or similar base inputs e.g. financial ratios and characteristics calculated for different time period using same underlying period.

If, for example, some highly correlated inputs are included in the model, we will encounter multicollinearity problem that leads decrease in explanatory variables statistical significance, wrong sings of coefficients and consequently incorrect conclusions about relationships between independent and dependent variables. In order to treat potential correlation between the variables, we reviewed correlation coefficient among independent variables manually. This is shown in attached excel file to the paper Appendix 1. As we see, there are higher correlations between individual variables, therefore, we can omit one of the highly correlated two or create variable combination to eliminate correlation between single variables. In our case, we decided to drop equity to total asset ratio, current asset to current liability ratio, EBIT to total asset and working capital to current liabilities ratios.

[7] Type 1 error and type 2 error were not high.

We will use Gretl statistical software for estimation of our model and our econometric model is specified as following:

$$\mathrm{Logit}(Y = 1) = \beta_0 + \beta_i X_i$$

Where i=1….15

As previously mentioned variables which have high correlation with each other we have left below fifteen variables.

Table 6: Ratios included in logistic regression

#	Ratios	
1	TL/TA	Total Liability/Total asset
2	TL/Tan A	Total Liability/Tangible asset
3	BD/TA	Bank debt/total asset
4	STD/TA	Short term debt/ total asset
5	R/NS	Account receiveable/ net sales
6	CA/TA	Current asset/TA
7	C/TA	Cash/ TA
8	CA/TS	Current asset/Net sales
9	C/CL	Cash/Current liabilities
10	NI/TR	Net income/Total op revenue
11	EBIT/E	EBIT/Equity=ROE
12	WC/TA	Working capital/Total Asset
13	RE/TA	Retained earnings /Total Asset
14	MVE/TL	Market value of equity/Total Liability
15	S/TA	Sales/Total asset

Estimating the independent variables through the logistic regression we will attempt to reach following goals:

- Using prepared 32 firms' data set and 16 ratios, we will identify statistically significant and unbiased parameters and build final model. When doing so, we could use one of two procedures, backward and forward selection to identify final model. Those are methods used to statistical stepwise variable selection and implemented in most of statistical software packages. For our data set, backward elimination will be applied. It will starts with estimating all possible input variables and move further by removing the worst ratios one by one until we come to model with all remaining explanatory variables are significant at chosen critical level. We can evaluate overall model as well as each independent variable's significance by using appropriate statistical tests.

- After that we will assess goodness of fit of the derived model. This can be accomplished by comparing actual outcomes with result of logistic regression model. We could use several statistics which can be applied for comparing alternative models or evaluating the performance of a single model such as percent of correct predictions, "pseudo-Rsq" Log likelihood tests.

Results of parameter estimation

In this section we will comment on overall results of the logistic regression analysis. As mentioned above the analysis will start with estimating full model, which includes all possible candidates for independent variables. The table 7 displays overall result of the estimated model, especially, coefficient estimates, standard errors, and p values. If we take a look at the estimated model, five independent variables are statistically significant on 90 percent level of confidence interval. As accepted widely, a major disadvantage of logistic regression is that the absolute magnitude of coefficients is not interpretable like it is in ordinary least squares regression models. Therefore, if we consider the postulated hypothesis based on economic sense of computed ratios, two of significant ratios are different than our expectation. More specifically, the log of the odds of a borrower being defaulted was negatively affected by total liability to tangible asset and positively related to cash to current liability ratio, respectively. It means that higher total liability to tangible asset ratio, the less likely it is the borrower would be defaulted and increase in cash to current liability ratio leads to increase in default probability. Those don’t make sense.

In terms of overall model evaluation, most common measure is McFadden R-squared. It is 63 percent in our model, which means the model fit is at satisfactory level as this value tends to be smaller than R-square in linear regression and values of .2 to .4 are considered highly adequate.

In addition to this, to evaluate goodness of fit for overall model we could use log likelihood ratio test. Basically, the test consists of comparing log likelihood statistics of a baseline null model, which is a model just has a constant, against full model with proposed independent variables.

The null hypothesis, H_0 indicates that all coefficients are equal to 0, or, all alternatives are equally likely to be chosen. $L_{(c)}$ is the log likelihood computed when all coefficients including alternative specific constants are constrained to be zero, and $L_{(b)}$ is the log likelihood computed with no constraints on the model. The test statistics is given by the formula $-2(L(b_c)-L(b))$ has a chi-square distribution with degrees of freedom equaling the number of constrained coefficients. For our model, test can be calculated as the formula -2*(-7,712213-(-21,17002))= 26,915614. The Gretl software gives us the same result with the calculated one, implying that chi square test result Chi-square (14) = 26,9156 with p_value=0,0197. Therefore we can reject the null hypothesis at 95 percent confidence level and conclude that overall model with all independent variable is significant.

Next indicator we should pay attention is that percent of correct predictions. This is given by the classification table which is available for all statistical software. Acceptable accuracy level is a practical consideration and depends on characteristics data. In our model the accuracy level is quite well and number of correctly predicted cases is depicted as 28 or 87.5 %.

Table 7: Model I : included all candidate independent variables

Model 1: Logit, using observations 1-32 Dependent variable: Actual_default QML standard errors Omitted due to exact collinearity: WC_TA

	coefficient	std.error	Z	p-value	Hypothesis
const	-1142,41	9812,82	-0,1164	0,9073	
TL_TA	1542,97	12747,8	0,121	0,9037	+
TL_Tan_A	-24,0303	13,2353	-1,816	0,0694 *	+
BD_TA	-333,967	2952,64	-0,1131	0,9099	+
STD_TA	-346,433	2941,37	-0,1178	0,9062	+
R_NS	-11,4046	13,7451	-0,8297	0,4067	+
CA_TA	-19,3398	13,2433	-1,46	0,1442	-
C_TA	-87,9181	46,7023	-1,883	0,0598 *	-
CA_TS	-1,29682	9,09021	-0,1427	0,8866	-/+
C_CL	6,77345	3,52815	1,92	0,0549 *	-
NI_TR	6,40070	11,3441	0,5642	0,5726	-
EBIT_E	-0,0438729	0,481026	-0,09121	0,9273	-
RE_TA	-17,2885	10,1964	-1,696	0,0900 *	-
MVE_TL	1179,41	9809,43	0,1202	0,9043	-
S_TA	-11,8506	6,73377	-1,76	0,0784 *	-

Mean dependent var 0,375000 S.D. dependent var 0,491869	Number of cases 'correctly predicted' = 28 (87,5%)
McFadden R-squared 0,635701 Adjusted R-squared -0,072848	f(beta'x) at mean of independent vars = 0,000
Log-likelihood -7,712213 Akaike criterion 45,42443	Likelihood ratio test: Chi-square(14) = 26,9156 [0,0197]

However general result of the model is acceptable, full model has number of insignificant variables and some estimated coefficient take signs which are economically meaningless. Therefore, we need to estimate alternative models to improve the results. We continue the model by omitting such kind of variables and have come with a following final model and its statistics are depicted in table 7. We come up with following model as final and statistics of the model are shown in table 8.

Predicted logit of (default)=0.601-8,14*Cash/TA- 3,42*Retained earnings /Total Asset

According to this model, cash to total asset and retained earning to total asset ratio are significant variables in predicting default probabilities for selected sample data at 95 percent confidence level. All signs of the coefficients correspond to the expected hypotheses. When we compare McFadden R squared, it is decreased dramatically in final model. However unlike in linear regression model, McFadden R squared is acceptable between 0.2-0.4. Result of the likelihood ratio test is Chi-square(2) = 12,3158 with p value=0,0021, which means we can not reject the null hypothesis that all coefficients are equal to zero and our final model is statistically significant as a whole. Number of cases correctly predicted was slightly decreased in the final model. Even though, it is still at acceptable level.

Table 8: Final model with two predictors

Model 5: Logit, using observations 1-32 Dependent variable: Actual_default QML standard errors

	Coefficient	Std. Error	z	p-value
const	0,601965	0,657107	0,9161	0,35962
C_TA	-8,14433	2,61951	-3,1091	0,00188***
RE_TA	-3,42008	1,44379	-2,3688	0,01784**
Statistics				
Mean dependent var	0,375	S.D. dependent var		0,491869
McFadden R-squared	0,290877	Adjusted R-squared		0,149167
Log-likelihood	-15,01214	Akaike criterion		36,02429
Schwarz criterion	40,4215	Hannan-Quinn		37,48184
f(beta'x) at mean of independent vars = 0,492			Predicted 0	1
Number of cases 'correctly predicted' = 21 (65,6%)		Actual 0	14	6
Likelihood ratio test: Chi-square(2) = 12,3158 [0,0021]		1	5	7

Comparison to Altman Z score results: Two variables included in final model are generally very similar to risk factors in Altman Z score. Cash to total asset ratio corresponds to working capital to total asset ratio. As the selected companies are SME companies and capital market development is not comparable to other developed economy, the most selected companies don't have other liquid asset than cash thus, it makes sense that cash on hand to total asset ratio is significant indicator in default prediction. Moreover, the descriptive statistics table described in section 4.1 shows that median and other statistics of these two ratios are very similar. Second significant ratio in the final model is retained earning to total asset ratio which is exactly same as in Altman-Z score model.

In terms of model accuracy, we look at classification table which consolidate number of correctly predicted cases. Gretl software computed this for us and result tells us how many of the cases where the observed values of dependent variable were one or zero respectively have been correctly predicted. According to Altman Z score overall 71 percent of total observations have correctly classified while logistic regression classifies correctly 66% of total cases. Moreover type 1 error, which means that percentage of wrong prediction of the model for bankrupted firms have increased dramatically to 41.7% in logistic regression model and type 2 error, that is expressed as proportion of incorrect prediction of the model for non-bankrupted firms decreased slightly to 30% from 40% (see Table 9)

Table 9: Prediction statistics of Altman Z score and Logit model

	Prediction statistics of Altman Z score and Logistic regression model							
	Bankrupted companies				Non-Bankrupted companies			
Model	All	Correctly classified	Type 1 error	% correct	All	Correctly classified	Type 2 error	% correct
Altman Z score	12	11	1	92%	20	12	8	60%
Logistic regression	12	7	5	58.3%	20	14	6	70%

Chapter5. Conclusion

Credit risk has been key issue in financial world and numbers of techniques have been developed in the credit risk and credit portfolio risk management field, including Basel II framework. Implementation of the new techniques in an effective and appropriate manner is a challenging task for commercial banks acting in developing economies like Mongolia where a commercial banking itself has not yet seen whole two decades. Moreover, increased competition and financial and economical turbulent environment are forcing the commercial banks to develop more efficient internal credit risk management processes in order to find the optimal mix between taking risks, maximizing returns and creating their own capital provisions. For that reason the diploma thesis put the goal to contribute to credit risk management practice.

The thesis consists of three chapters which have divided in two broad categories, theoretical and practical. In the first chapter we have provided overview of credit risk and capital accord of Basel II. Credit risk definition, main sources, credit risk management principles as well as Pillars in Basel II accord are discussed briefly in this chapter.

In second chapter we have paid to attention on the credit risk assessment approaches. We start with reviewing traditional credit scoring models such as expert system, rating system and credit scoring models. The traditional approaches are mainly developed based on accounting based ratios and focus more on probability default predictions. There are number of drawbacks for this type of methods, a major belief under the approaches is that annual financial statements include the necessary information to predict financial of the firm in the future. However, as capital market development grows, the belief has started to fail to acknowledge the market frequent information because accounting statements are prepared by limited time and number of experts. Besides these traditional credit risk methods, modern methods were the subsection of this chapter. Under structural models, Merton's KMV model is examined and for reduced form model we have studied KPMG credit risk methodology. The chapter has ended with Credit value at risk approach.

Third chapter is devoted to practical section as a whole. In the practical section, we have set a goal to compare Altman-Z score model to the model which is developed by me using logistic regression method. First, we computed Altman's Z score for 32 small and medium sized firms in Mongolia. Dataset used in the practical section was taken from a Mongolian commercial bank. Altman's Z score model prediction accuracy was considerably high for selected sample resulting correctly predicted firms are 71% of total sample. Using prepared data for 2008 which is one year prior to bankruptcies, we have calculated overall 19 financial ratios and 14 ratios were selected to estimation of final model. The estimation of logistic regression reveals that cash to total asset ratio and retained earnings to total asset ratios are statistically significant for predicting default probabilities. Compared to Altman Z score model, overall accuracy of the estimated final model is slightly decreased to 66%. Taking into account type-two errors, Altman's Z score model were preferable resulting considerably low, 2 percent.

Appendixes

Appendix 1: Correlation coefficients between independent variables

	Total Liability/Total asset	Total Liability/Tangible asset	Bank debt/total asset	Short term debt/ total asset	Account receiveable/ net sales	Current asset/TA	Cash/ TA	Current asset/Net sales	Cash/Current liabilities	EBIT/Total asset=ROA	Net income/Total op revenue	EBIT/Equity=ROE	WC/TA	RE/TA	MVE/TL	Sales/TA
Total Liability/Total asset	1,0															
Total Liability/Tangible asset	- 0,2	1,0														
Bank debt/total asset	0,2	0,2	1,0													
Short term debt/ total asset	0,8	- 0,2	0,4	1,0												
Account receiveable/ net sales	- 0,0	- 0,2	0,3	0,0	1,0											
Current asset/TA	- 0,0	- 0,7	- 0,3	0,1	0,4	1,0										
Cash/ TA	- 0,2	- 0,3	- 0,3	- 0,2	- 0,5	0,3	1,0									
Current asset/Net sales	- 0,2	- 0,2	0,1	- 0,2	0,5	0,3	0,2	1,0								
Cash/Current liabilities	- 0,5	- 0,0	- 0,2	- 0,4	- 0,3	0,3	0,7	0,2	1,0							
EBIT/Total asset=ROA	- 0,5	0,3	0,1	- 0,4	0,1	0,0	0,0	0,1	0,2	1,0						
Net income/Total op revenue	- 0,2	0,2	- 0,0	- 0,1	0,1	0,1	- 0,2	- 0,4	0,1	0,4	1,0					
EBIT/Equity=ROE	- 0,1	0,2	- 0,1	- 0,0	0,1	- 0,0	- 0,3	- 0,1	0,1	0,0	0,7	1,0				
WC/TA	- 0,9	- 0,0	- 0,0	- 0,8	0,2	0,3	0,3	0,4	0,5	0,5	0,2	0,1	1,0			
RE/TA	- 0,5	0,3	- 0,0	- 0,4	0,1	- 0,0	- 0,1	0,0	0,2	0,7	0,8	0,7	0,5	1,0		
MVE/TL	- 0,9	0,2	0,1	- 0,6	0,1	- 0,0	0,2	0,2	0,4	0,5	0,2	0,1	0,9	0,4	1,0	
Sales/TA	0,3	- 0,2	0,4	0,7	- 0,2	0,1	- 0,2	- 0,5	- 0,2	- 0,2	0,2	0,1	- 0,3	- 0,2	- 0,2	1,0

Appendix 2: Comparison of Logit estimates Dependent variable: Actual_default

Model #	(1)	(2)	(3)	(4)	(5)
const	-1142	-0,9682	-1,090	0,5977	0,6020
	(9813)	(1,970)	(1,394)	(0,6545)	(0,6571)
TL_TA	1543	3,699*	3,066		
	(1,275e+04)	(1,952)	(2,030)		
TL_Tan_A	-24,03*				
	(13,24)				
BD_TA	-334,0				
	(2953)				
STD_TA	-346,4				
	(2941)				
R_NS	-11,40				
	(13,75)				
CA_TA	-19,34	0,7406			
	(13,24)	(2,118)			
C_TA	-87,92*	-18,05**	-15,31**	-7,320	-8,144**
	(46,70)	(8,540)	(6,437)	(4,561)	(2,620)
CA_TS	-1,297				
	(9,090)				
C_CL	6,773*	1,196*	1,010*	-0,2038	
	(3,528)	(0,7109)	(0,5621)	(0,8869)	
NI_TR	6,401				
	(11,34)				
EBIT_E	-0,04387				
	(0,4810)				
RE_TA	-17,29*	-5,548**	-4,739**	-3,255*	-3,420**
	(10,20)	(2,563)	(2,097)	(1,715)	(1,444)
MVE_TL	1179				
	(9809)				
S_TA	-11,85*	-0,6223			
	(6,734)	(0,4940)			
n	32	32	32	32	32
Adj. R^2	0,6357	0,4102	0,3859	0,2922	0,2909
lnL	-7,712	-12,49	-13	-14,98	-15,01

Standard errors in parentheses, * indicates significance at the 10 percent level For logit and probit, R^2 is McFadden's pseudo-R^2

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