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# FINANCIAL SOUNDNESS OF KAZAKHSTAN BANKS: ANALYSIS AND PREDICTION

**AIGUL P. SALINA**

**PhD** **2017**

# FINANCIAL SOUNDNESS OF KAZAKHSTAN BANKS: ANALYSIS AND PREDICTION

**AIGUL PAZENOVNA SALINA**

**A thesis submitted in partial fulfillment**
**of the requirements of**
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**for the degree of DOCTOR OF PHILOSOPHY**

**December, 2017**

## CERTIFICATION

I, Aigul Pazenovna Salina, declare that this thesis, submitted in fulfillment of the requirements for the award of Doctor of Philosophy, at the Aberdeen Business School of the Robert Gordon University, is wholly my own work unless otherwise referenced or acknowledged. The document has not been submitted for qualifications at any other academic institution.

Aigul Pazenovna Salina

Aberdeen, December, 2017

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**CONTENTS**

**FINANCIAL SOUNDNESS OF KAZAKHSTAN BANKS: ANALYSIS AND PREDICTION**

## ABSTRACT

**Purpose –** The financial systems in many emerging countries are still impacted by the devastating effect of the 2008 financial crisis which created a massive disaster in the global economy. The banking sector needs appropriate quantitative techniques to assess its financial soundness, strengths and weaknesses. This research aims to explore, empirically assess and analyze the financial soundness of the banking sector in Kazakhstan. It also examines the prediction of financial unsoundness at an individual bank level using PCA, cluster, MDA, logit and probit analyses.

**Design/Methodology/Approach –** A cluster analysis, in combination with principal component analysis (PCA), was utilized as a classification technique. It groups sound and unsound banks in Kazakhstan's banking sector by examining various financial ratios. Cluster analysis was run on a sample of 34 commercial banks on 1st January, 2008 and 37 commercial banks on 1st January, 2014 to test the ability of this technique to detect unsound banks before they fail. Then, Altman Z” and EM Score models were tested and re-estimated and the MDA, logit and probit models were constructed on a sample of 12 Kazakhstan banks during the period between 1st January, 2008 and 1st January, 2014. The sample consists of 6 sound and 6 unsound banks and accounts for 81.3% of the total assets of the Kazakhstan banking sector in 2014. These statistical methods used various financial variables to represent capital adequacy, asset quality, management, earnings and liquidity. Last but not least, the MDA, logit and probit models were systematically combined together to construct an integrated model to predict bank financial unsoundness.

**Findings –** First of all, results from Chapter 3 indicate that cluster analysis is able to identify the structure of the Kazakh banking sector by the degree of financial soundness. Secondly, based on the findings in the second empirical chapter, the tested and re-estimated Altman models show a modest ability to predict bank financial unsoundness in Kazakhstan. Thirdly, the MDA, logit and probit models show high predictive accuracy in excess of 80%. Finally, the model that integrated the MDA, logit and probit types presents superior predictability with lower Type I errors.

**Practical Implications –** The results of this research are of interest to supervisory and regulatory bodies. The models can be used as a reliable and effective tool, particularly the cluster based methodology for assessing the degree of financial soundness in the banking sector and the integrated model for predicting the financial unsoundness of banks.

**Originality/Value –** This study is the first to employ a cluster-based methodology to assess financial soundness in the Kazakh banking sector. In addition, the integrated model can be used as a promising technique for evaluating the financial unsoundness of banks in terms of predictive accuracy and robustness.

**Importance** – Assessing the financial soundness of the Kazakh banking system is of particular importance as the World Bank has ranked Kazakhstan as leading the world for the volume of non-performing credits in the total number of loans granted in 2012. It is one of the first academic studies carried out on Kazakhstan banks which comprehensively evaluate the financial soundness of banks. It is anticipated that the findings of the current study will provide useful lessons for developing and transition countries during periods of financial turmoil.

## LIST OF ABBREVIATIONS

| | |
|---|---|
| ADB | Asian Development Bank |
| AFS | Agency on Regulation and Supervision of Financial Market and Financial Organizations of Kazakhstan |
| AIES | Artificially Intelligent Expert System |
| ANN | Artificial Neural Networks |
| BCBS | Basel Committee on Banking Supervision |
| BCP | Best Current Prices |
| BIS | Banks for International Settlements |
| CAR | Capital Adequacy Ratio |
| CART | Classification and Regression Trees |
| CIS | Commonwealth of Independent States |
| DA | Discriminant Analysis |
| DEA | Data Envelopment Analysis |
| DER | Debt to Equity Ratio |
| EAEU | Eurasian Economic Union |
| EBIT | Earnings Before Interest andTax |
| EFSF | European Financial Stability Facility |
| EMU | Economic and Monetary Union |
| Eviews | Econometric Views |
| EWS | Early Warning System |
| FDIC | Federal Deposit Insurance Corporation |
| FSI | Financial Soundness Indicators |
| GDP | Gross Domestic Product |
| GFSR | Global Financial Stability Report |
| IAS | International Accounting Standards |
| IEWS | Integrated Early Warning System |
| IFRS | International Financial Reporting Standards |
| IMF | International Monetary Fund |

| | |
|---|---|
| Kazakh SSR | Kazakh Soviet Socialist Republic |
| KMO | Kaiser - Meyer – Olkin |
| k-NN | K-Nearest Neighbors |
| LR | Likelihood Ratios |
| MCDA | Multi-Criteria Decision Analysis |
| MDA | Multivariate Discriminant Analysis |
| MDDM | Merton Distance to Default Model |
| MRR | Minimal Reserve Requirements |
| NB RK | National Bank of the Republic of Kazakhstan |
| NPL | Non-Performing Loan |
| NYSE | NewYork Stock Exchange |
| OECD | Organization for Economic Cooperation and Development |
| OLR | Ordered Logistic Regression |
| OREO | Ratio of Other Real Estate Owned |
| PCA | Principal Component Analysis |
| PHM | Proportional Hazard Model |
| ROA | Return on Assets |
| ROE | Return on Equity |
| RQ | Research Questions s |
| SB | Subsidiary Bank |
| SCOR | Statistical CAMELS Off-Site Rating |
| SEER | System for Estimating Exam |
| SFA | Stochastic Frontier Analysis |
| SIFIs | Systemically Important Financial Institutions |
| SME | Small and Medium-Sized Enterprises |
| SPS | Sanitary and Phyto-Sanitary |
| SPSS | Statistical Package for the Social Sciences |
| SSR | Social Soviet Republic |
| STB | Second Tier Banks |

| | |
|---|---|
| TARP | Troubled Asset Relief Program |
| UFIRS | Uniform Financial Institutions Rating System |
| USSR | Union of Soviet Socialist Republics |
| UTADIS | UTilite´s additives DIScriminantes |

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## CHAPTER 1 INTRODUCTION

### 1.1 Introduction

The recent financial crisis of 2008 showed the crucial importance of the concept of ‘‘well-being’’ in the economy. It started in developed countries and influenced them adversely in a number of ways[1.] Unemployment increased substantially, investment and consumption decreased and some governments had to take decisive measures to restructure the debt and partially nationalize several banks (Ioannidis et al., 2010). Developed economies have largely overcome the crisis, while many developing countries are still in stagnation, especially Kazakhstan (IMF, 2014). The devastating effects of the crisis demonstrated the need for early detection of vulnerable banks to avoid such problems in the future. Regulators, supervisory and monitoring bodies need appropriate instruments to detect the financial unsoundness of the banks. Key prior studies have moved that statistical models have high predictive power in detecting early warning signals of deterioration in bank performance.

Recently many academicians and practitioners from both developed and emerging countries have used statistical models to detect financial turmoil in the banking sector. The International Monetary Fund (IMF) in 2006 proposed a set of Financial Soundness Indicators (FSI) that measure the health of a country’s financial system. Since then, many multi-country studies have explored the financial soundness of banks (Čihák and Schaeck, 2007, Babihuga, 2007, Davis and Karim, 2008, Ioannidis et al., 2010, Navajas and Thegeya, 2013, Bourkhis and Nabi, 2013 and Camelia and Angela, 2013), while a few have investigated the financial soundness of banks at an individual country level (Gasbarro et al., 2002, Safdari, Scannell and Ohanian, 2005, Şchiopu, 2010, Abudu, 2011, Dao and Khanh, 2014 and Ginevicius and Podviezko, 2013).

The Altman models were widely used to predict bankruptcy, failure (Agarwal and Taffler, 2008), distress (e.g., Coats and Fant, 1993; Grice and Ingram, 2001; Chieng, 2013) and default (e.g., Allayannis et al., 2003; Sueyoshi and Goto, 2012; Othman, 2013; Castagnolo and Ferro, 2014 and Hogan, 2014). Many studies re-estimated the Altman models to improve their predictability such as those by Moyer (1977), Coats and Fant (1993), Begley et al. (1996), Grice and Ingram (2001), Wu et al. (2010) and Ho et al.

1 Most prior large-scale banking crisis have had their origins in developed countries, for example, in the United States of America (USA) - the“Great Depression” in 1929-1939;  in Europe, the Secondary Banking Crisis and Property Crash in 1973-1975; in USA “Black Monday” in 1987, and the Subprime Global Financial Crisis in 2008 (Corpoasia, 2016). However, some large-scale banking crises have had their origins in developing countries such as the Mexican crisis in1994, the Asian Financial Crisis in 1997, the Russian Financial Crisis in 1998 (Caprio G, Klingebiel D, 2003)

(2013). However, most previous studies employed the Altman models on samples from developed countries (e.g., Griffin and Lemmon, 2002, Agarwal and Taffler, 2008, Xu and Zhang, 2009, Wu et al., 2010, Ho et al., 2013, Chieng, 2013, Hogan, 2014) and fewer studies have been conducted in emerging countries.

Furthermore, statistical methods such as MDA, logit and probit models were successfully used to predict bankruptcy or bank distress in prior studies (e.g., Meyer and Pifer, 1970, Espahbodi, 1991, Catanach and Perry, 2001, Canbas, Cabuk and Kilic, 2005, Ioannidis, Pasiouras and Zopounidis, 2010, Othman, 2013, Betz et al., 2014, Mitchell, 2015 and Kimmel, Thornton Jr. and Bennett, 2016). Previous studies confirmed that statistical models have high predictive accuracy to detect and predict financial unsoundness. However, the vast majority of the literature on bank failure refers to western countries, especially the USA (about 65% from all reviewed studies, as will be discussed in Chapter 5). Fewer studies have been devoted to detecting bank financial soundness using these statistical models in developing countries (Rahman et al., 2004, Canbas, Cabuk and Kilic, 2005 and Othman, 2013) and even fewer studies are conducted in post-soviet countries, mostly for Russia (Kuznetsov, 2003 and Golovan et.al, 2003).

The Kazakhstan banking sector has attracted some studies but they are mostly at a multi-country level (Hoelscher, 1998, Fries and Taci, 2005, De Haas, Ferreira and Taci, 2010 and Delis, Molyneux and Pasiouras, 2011). To the best of the researcher's knowledge, there is only one prior study (Glass, Kenjegalieva and Weyman-Jones, 2013) that analyses the performance of the entire Kazakh banking industry for the period March 2007 – December 2010, using the Stochastic Frontier Analysis (SFA).

This study analyses the performance of the Kazakhstan banking sector in order to detect early warning signs of deterioration in individual bank financial soundness. The objectives are: (i) to identify the structure of the Kazakhstan banking sector by the degree of financial soundness; (ii) to examine the ability of the Altman, Multiple Discriminant Analysis (MDA), logit and probit models to predict bank financial unsoundness (iii) to develop a model which would detect future unsoundness with a high predictive accuracy and (iv) to advance our knowledge about the financial soundness of banks in developing countries with reference to Kazakhstan. It is one of the first academic studies carried out for Kazakhstan banks which comprehensively evaluates bank financial soundness. It is anticipated that the findings of the current study will provide useful lessons for developing and transition countries during periods of financial turmoil.

### 1.2 Motivations and Contributions of the Current Study

The world economy has been in a state of fragility since the outbreak of the global financial crisis. While some countries navigated the crisis with relative success and staged strong recoveries, many banking systems of emerging countries are still struggling. Therefore, the need for early warning signals of potential shocks in the banking sector has become increasingly important. In this context, and as a consequence many academicians and practitioners try to develop reliable tools to assess bank financial soundness (Navajas and Thegeya, 2013).

The deep transformational crisis of the 1990s and the crushing of the entire political, economic and social structure of Kazakh society after the breakup of the USSR did not allow the economy to achieve sustainable development. From the end of the late 1990s to 2008, Kazakhstan experienced a powerful leap forward. For the first time in many years, there had been formulated ambitious objectives, the achievement of which was assumed to provide modernization of not only the economy but also society. The global financial crisis of 2007 created devastating losses. The banking system of Kazakhstan was considered one of the most efficient in the Commonwealth of Independent States (CIS), yet it has been in deep recession and virtually collapsed (Seyitkasimov, 2010).

According to Asia Development Bank (ADB, 2015) the recent financial crisis revealed the weakness of the majority of the banking systems in developing countries. These include the banking sector’s predominance in financial intermediation; the lack of long-term credit facilities; the underdevelopment of capital markets; a lack of a strong domestic credit rating system; insufficient skilled financial operatives and agents; a reliance on weak accounting and reporting standards; and weaknesses in regulatory and supervisory frameworks. Also, there has been weak risk management, a high level of non-performing loans (NPL) and “*special interest groups that have influenced credit to be channeled to unprofitable and unproductive use*” (ADB, 2015, p. xiii).

Mingaleva et al (2014), analysing the reasons of non-performing loans in some countries, noted that there are special factors which impact greatly on the dynamics and size of NPL. In Kazakhstan this special factor is frauds. The key reason which led to the existence of these types of actions is the lack of transparency and information asymmetry between the debtors and creditors. This allowed the execution of the lending transactions to the parties directly related to the shareholders or management, ignoring the riskiness and validity of the projects. The result is that bribes let questionable loans be granted and the latter are soon turning into NPL. By experts' estimates, 85% of all the non-performing loans in

Kazakhstan are the product of fraudulent activity. The most damaged parties in this situation have been foreign investors who lost about 15 billion dollars (Mingaleva et al, 2014).

As of 2007, the share of banking sector assets in Gross Domestic Product (GDP) in Kazakhstan amounted to 91% which roughly corresponded to the average of the countries of Eastern and Central Europe. Unfortunately, since 2008, the proportion of bank assets in GDP has been steadily dropping from 74% in 2008 to 68% in 2009, 55% in 2010, 59% in 2011, 46% in 2012 and 44% in 2013.The highest ratio of assets to GDP in 2013 was in Luxembourg at 1,575%, in Ireland at 424% and the United Kingdom at 375% (www.helgilibrary.com).

In addition, as of 2007, the ratio of bank loan portfolio to GDP was 69%, whereas at the beginning of 2014 it decreased to 38% and the ratio of customer deposits to GDP was 50% and fell to 28%.

Financial crises always lead to great losses in the economy. For example, Caprio and Klingebiel (1996) estimated the average costs of crises from 10% to 37% of GDP. Hoggarth, Reis and Saporta (2001) calculated cumulative output losses from crises at around 15% to 20% of annual GDP. They noted that developing economies generally recovered slowly because they have more problems with nonperforming loans than developed countries.

In Kazakhstan, the level of non-performing loans (NPL) dramatically increased from 2.4% in 2007 to 36% in 2013. The World Bank summarizing the results for 2012 on most economies in the world ranked Kazakhstan first according to the amount of non-performing loans in the total number of loans extended (Vorotilov, 2013). To date, Kazakhstan seems to have failed to resolve its loan problems. According to the IMF report the recovery of financial system of Kazakhstan from the crisis is not yet complete (IMF, 2014). Its banking sector is vulnerable and highly risky due to low asset quality and high dollarization as well as other post-soviet countries such as Russia, Ukraine, Belarus and Azerbaijan (Sberbank of Russia, 2012).

All of the aforesaid issues have been a powerful motive for undertaking this research. This requires a comprehensive and reliable assessment of the banking sector as a whole according to the degree of financial soundness and to predict the financial unsoundness of individual banks. In this context, this study contributes to the literature in several aspects.

Firstly, previous research review showed that there are many of studies on the assessment of the financial soundness of the banking systems at the cross-country level, but there is a lack of research that comprehensively assesses the financial soundness of the banking sector in an individual country. This study seeks to fill this gap by developing a cluster based methodology to identify the structure of the entire banking sector by the degree of financial soundness.

Secondly, the majority of the literature on bank failure prediction refers to western countries, especially the USA. Studies devoted to developing countries, particularly post-soviet, are still lacking. This study aims to fill this gap by designing prediction models of bank unsoundness on a sample of sound and unsound Kazakhstan banks.

Thirdly, the findings of the current study are expected to be beneficial for the banking systems in developing countries in general and, in particular for the post-soviet countries, to which Kazakhstan relates. In addition, the Kazakhstan banking sector is in an infant stage of development. Regulatory and supervision bodies need suitable and reliable early warning tools to predict bank unsoundness in the young post-soviet banking systems in general and in Kazakhstan in particular, where a strong banking sector is still lacking.

As a practical contribution, the proposed cluster based methodology of financial soundness assessment will identify the structure of the banking sector and help monitor its changes. In addition, a suggested integrated prediction model of financial unsoundness will serve as an early warning instrument to detect the first signals of potential failure of commercial banks in Kazakhstan.

### 1.3 Research Questions

The main purpose of this study is to explore, empirically assess and analyse the financial soundness of the banking sector of Kazakhstan and predict the financial unsoundness of individual banks using a variety of research methods.

To accomplish this purpose, it is necessary to address the following research questions:

1. Can cluster analysis identify the structure of the banking sector according to the extent of financial soundness?
2. Can Altman's models adequately predict bank financial unsoundness?
3. Can the predictability of bank financial unsoundness be improved by using statistical models such as MDA, Logit and Probit?

## 1.4 Research Methods

The research methods used in the current study are developed based on a review of previous studies that are relevant to each of the addressed research questions.

The current research focuses particularly on the Kazakhstan banking sector and uses different research methods and different samples sizes to answer the different research questions.

Chapter 3 answers the first research question and assesses the banking sector by the degree of financial soundness using a combination of principal component analysis (PCA) and cluster analysis. The PCA was carried out on the annual data for the period from 1st January, 2008 to 1st January 2014 from all commercial Kazakhstan banks. The number of banks changed from 34 at 1st January, 2008 to 37 at 1st January 2014 which accounts for 256 observations in total. Then, cluster analysis was applied at two points in time on January 1, 2008 and January 1, 2014. These dates were considered with the aim of examining the evolution of clusters over time. The former date represents the pre-crisis period and the latter was taken as the final most recent date with the fully available data. The analysis was carried out for all 34 banks on 1st January, 2008 and 37 banks on 1st January, 2014.

The Cluster based methodology applied in Chapter 3 has identified 6 unsound banks. Then 6 sound banks were selected after taking into account their assets' size, specializations and branch networks. The test sample contains 12 banks and their share of assets in the total assets of the banking sector at 81.3%. Since sound and unsound groups of banks were defined on 1st January, 2014, this date is used as a benchmark for the application of Altman, MDA, logit and probit models. In Chapter 4, Altman Z and EM Score were tested and re-estimated on the annual data for the period from 1st January, 2008 to 1st January 2014 (84 observations).

In Chapter 5, MDA, logit, and probit models are developed using same sample of 12 banks as Chapter 4 for the same period but this period was divided into 2 parts for the last models: in-sample period from 1st January, 2008 to 1st January 2012 (60 observations) and out-sample period from 1st January, 2012 to 1st January 2014 (24 observations). Data was collected from the reports of the National bank of Kazakhstan and from the annual financial reports of all commercial Kazakhstan banks. This study is designed as three separate research papers with their own abstract, literature review, research methodology, empirical results and summary. Links between research structure, applied methods and chapters are shown in Table 1.1.

**Table 1.1: Relationship between Research Structure, Methods and Chapters**

| Research Structure | Methods Used | Chapter |
|---|---|---|
| Definition of financial soundness | Literature review | Chapter 3 |
| Statistical methods and models used by prior studies to analyze financial soundness of banks | Literature review | Chapter 3, 4, 5 |
| Identification of a the set of financial variables that could be used to assess financial soundness at the macro and micro levels | Literature review | Chapter 3 |
| Cluster analysis to assess the financial soundness of the Kazakhstan banking sector. | PCA , Cluster Analysis | Chapter 3 |
| An assessment of the financial soundness of the Kazakhstan banks using a variety of models. | Altman Z and EM Score models, MDA, Logit, Probit Analysis, Integrated model | Chapters 4, 5 |

**Source:** Author

In this research the Statistical Package for the Social Sciences (SPSS) version 21 and Econometric Views (Eviews) version 8 are used.

### 1.5 The Structure of the Research

The research consists of an introduction, a study of the current state of Kazakhstan's banking sector, three empirical chapters and conclusions.

The first chapter, as an introduction, describes the motivation of the research study, the research questions, the research methods, the contribution of the research study and the structure of research.

The second chapter describes the historical and economic development of Kazakhstan with a history of its banking system formation, the current state of the banking sector and its regulation.

The third chapter is the first empirical part of the research, which analyzes the secondary data collected about the Kazakhstan banks, based on the selected set of variables and to set the limits of financial soundness. The chapter proposed the use of a cluster based methodology of assessing of the financial soundness of the banking sector and identified its structure according to the extent of financial soundness.

The fourth chapter tests the ability of Altman's Z (1993) and EM Score (1995) models on detecting and predicting the financial unsoundness of Kazakhstan banks. The original models were re-estimated by the Direct and Wilk's methods.

The fifth chapter applies the MDA, Logit and Probit models. Then an integrated prediction model of bank financial unsoundness, based on these three models, was proposed to improve the accuracy of prediction of bank financial unsoundness.

Chapter 6 summarizes the study and provides answers to the key research questions, suggests the recommendations for applying the results of the research study, stipulates the research limitations and outlines the possibilities of further study.

# CHAPTER 2 THE BANKING SECTOR OF KAZAKHSTAN

## 2.1 Introduction

Kazakhstan is a post-soviet developing country that is transforming its economy from central planning to free-market. The Kazakh banking system has weaknesses and vulnerable areas in all of its developing financial systems. Their general hallmarks are reliance on weak accounting and reporting standards, weaknesses in regulatory and supervisory frameworks and inadequate corporate governance. The banking sector predominates in financial intermediation and the capital markets are underdeveloped. Banks lack long-term funding and skilled financial operatives (ADB, 2015). Kazakhstan provides a suitable context in which to investigate the issues of the financial soundness of a banking system for a number of important reasons.

First, the country is located in the centre of the Eurasian continent and its active participation in world affairs is a prerequisite for sustainable and secure development because it is a direct participant in the processes of reform. After more than 20 years of independence, Kazakhstan has become a member of many international organizations including the International Monetary Fund, the International Bank for Reconstruction and Development, the International Development Association, the Multilateral Investment Guarantee Agency, the International Finance Corporation and others. Moreover, such participation is another confident step towards acceptance of the country in the world and proof of the aspiration of Kazakhstan to be actively involved in global issues.

The financial sector and in particular the banking system of Kazakhstan is one of the most developed in the Central Asian region and it occupies a leading position in the post-soviet era. The global financial crisis has significantly affected the condition of the banking system in Kazakhstan and its consequences still affect negatively on economic stability.

Second, the last financial turmoil has highlighted the crucial importance of banking performance and, in particular, the need for comprehensive assessment of banking sector financial soundness and the prediction of individual banks' status in the area. Assessment of financial soundness provides early warning signs about any deterioration in the banking sector carried out using PCA and cluster analysis. It identifies the indicators that influence the financial soundness of banks, it classifies banks by degree of soundness and records changes of the banking sector structure. The prediction of bank financial unsoundness was derived using statistical methods such as MDA, logit and probit.

Thirdly, the financial sector of Kazakhstan, its condition, regulation and other characteristics have not been studied or covered properly in academic papers. The Kazakhstan banking sector as the object of study was analyzed mostly on a cross-country level (Hoelscher, 1998, Fries and Taci, 2005, De Haas, Ferreira and Taci, 2010 and Delis, Molyneux and Pasiouras, 2011) and only one study analyzed the banking industry on a country level (Glass, Kenjegalieva and Weyman-Jones, 2013).

In this chapter the current state of the banking sector was analyzed in detail from 2006 to 2014 taking into account the historical and economic development of Kazakhstan since independence.

Section 3.2 outlines the historical and economic development in Kazakhstan. Section 3.3 presents the development and formation of the banking system in line with the evolution and formation of Kazakhstan as a sovereign state and Section 3.4 describes the current conditions and prospects for development of the banking system to evaluate its financial soundness and the basic challenges faced by Kazakhstan's banks following the global financial crisis. Section 3.5 briefly characterises the regulation of the banking sector and Section 3.6 presents a summary of this chapter.

### 2.2 Historical and Economic Development of Kazakhstan

The history of Kazakhstan gives an understanding of the nature of its economic and financial development and focuses on the important aspects of the Kazakh national character. Both of these have implications for the financial system of the country. Since 1995 the quality of the banking sector has improved due to considerable consolidation with about 200 banks in 1993 falling to 38 in 2014.

In the short historical period from independence in 1991 the GDP per capita has increased 8.7 times from US$1,512 to $13,172 in 2013 (World Bank, 2014), which is a phenomenal result even in comparison with the swiftly developing southeastern "tigers" economies. The country is in the upper middle-income group of countries as per the World Bank’s classification. In the Bank’s “Doing Business” ranking of 2014 Kazakhstan occupied 50th place ahead of all CIS countries.

#### 2.2.1 Historical Background

The Kazakh Khanate was formed in the middle of the 15th century. At the beginning of the 18th century raids by the Jungar tribes became more frequent. In this difficult economic and political situation the question of joining with Russia was contemplated for the next

150 years. After the Russian Revolution of 1917 Soviet power was established in Kazakhstan. In 1991 the Kazakh Soviet Socialistic Republic was transformed into the Republic of Kazakhstan and its independence was proclaimed. Historically Kazakhstan has particularly close relationships with Russia. Corzine (1997) pointed out that, during the Cold War era, the Republic of Kazakhstan supplied many types of natural resources such as pure uranium, metals, oil and gas, etc. to the soviet military industrial complex in Russia and the Ukraine. 60% of the country's enterprises were involved in the military industrial complex and there was a sharp decline in industrial output after the dissolution of the former Soviet Union (FSU). Indeed, according to the Russian Petroleum Investor (1996a), in 1991 more than 40% of Kazakhstan's enterprises declared losses and most operated at 30-60% of their capacity due to broken business links with Russia.

In July 2010 a Customs Union of Belarus, Kazakhstan and the Russian Federation was launched and since January 1, 2012 the Single Economic Space between these countries has functioned and which Kyrgyzstan joined in 2014. This union is aimed at effectively developing the economy of the state participants and increasing the population's living standard based on the principle of the free movement of goods, services, financial and human capital through the borders of the four countries.

The Kazakh government is working to deepen integration in trade and to reduce the costs between the countries. Also, a key area is the reduction of nontariff barriers (NTBs) and technical regulations, including sanitary and phyto-sanitary (SPS) measures, which are significant cost-increasing barriers on their exports to Russia (World Bank, 2012).

### 2.2.2 Economic Background

Kazakhstan has a population of 17.4 million[2], located in the centre of the Eurasian continent. Occupying 2,724,900 square kilometres the country is ranked ninth by area among world states. In the north and west the Republic has a common border with Russia of 7,591 km which is the longest continuous land border in the world. Boarders are located in the east with China of 1,783 km, in the south with Kyrgyzstan of 1,242 km, with Uzbekistan of 2,351 km and with Turkmenistan of 426 km. The total length of land borders is 13,200 km. In addition, the Republic is bounded by the inland Caspian and Aral seas. Kazakhstan is the largest country in the world that does not have direct access to the world's oceans (Yesentugelov, 2008).

Kazakhstan's principal economic comparative advantage has been the abundance and

[2] Committee on Statistics of the Republic of Kazakhstan. www.stat.gov.kz

diversity of its natural resources. According to the BP Statistical Review of World Energy in June 2017 of by British Petroleum, at the end of 2016, proven oil reserves in Kazakhstan are 30 billion barrels. It is noted that in 2005 they were estimated at 9 billion barrels, and in 1995 - 5.3 billion. At the same time, oil production in Kazakhstan is 1,672 thousand barrels per day (British Petroleum, 2017).

According to the data of the Committee of Geology and Subsoil Use of Kazakhstan country has a variety of minerals. 99 of the 105 elements of the periodic table found in Kazakhstan and 70 have been explored, more than 60 elements are involved in commercial production.

**Table 2.1: Reserves of natural resources of Kazakhstan**

| Natural Resources | Unit | Explored Reserves | Estimated Value, billion $ |
|---|---|---|---|
| Chromium | Million tons | 350 | 972.2 |
| Lead | Million tons | 14.8 | 34.9 |
| Zinc | Million tons | 34 | 73.2 |
| Uranium | Thousand tons | 900 | 143.4 |
| Copper | Million tons | 40 | 353 |
| Gold | Tons | 902 | 95 |
| Natural gas | Billion $m^3$ | 1,830 | 274.5 |

**Source:** https://forbes.kz/stats/ostatochnyie_yavleniya

Kazakhstan is the first in the world in proven reserves of zinc, tungsten, and barite, the second - silver, lead and chromate, the third - copper and fluorite, the fourth - molybdenum, sixth - gold.

By volume of mineral resources, Kazakhstan is the first among the CIS countries in chrome ores and lead, the second - on oil, silver, copper, manganese, zinc, nickel and phosphate raw materials, the third - by gas, coal, gold and tin (Committee of Geology and Subsoil Use of Kazakhstan, 2017).

The decline in oil prices has affected the prospects for economic growth in Kazakhstan. Standard & Poor's list downgraded the sovereign rating of Kazakhstan from BBB + to BBB after the drop in oil prices. It forecasted a decline in demand for loans from small and medium-sized businesses and consumers due to the slowdown in GDP growth. Low world oil prices and the depreciation of the tenge increased the risk for Kazakh banks of a liquidity shortage, so reducing the growth of company and individual deposits.

Traditionally, great attention in the country is paid to the development of agriculture. Kazakhstan is one of the world's leading grain and flour exporters. Crops such as wheat, barley and millet occupy 70% of the arable land in the north. Rice, cotton and tobacco are grown in the south and Kazakhstan is famous for its orchards, vineyards and melon cultures. Animal husbandry remains a leading branch of agriculture with key areas in the breeding of cattle, horses, camels and pigs. In the Republic poultry and fishery are also developed.

Since independence the development of the industrial and agricultural sectors of the Kazakhstan economy has occurred along with the expansion of the financial services sector, including banking.

### 2.3 Banking Systems of Commonwealth of Independent States

Given the historical links and geographic proximity, developments in Kazakhstan are strongly affected by the economies of Commonwealth of Independent States (CIS) countries rather than the Eurasian region.

For analytical purposes, the United Nations in its World economic situation prospects (WESP) classified all countries of the world into one of three broad categories: developed economies, economies in transition and developing economies. Economies in transition are divided into two groups: South-Eastern Europe and Commonwealth of Independent States and Georgia. Group of CIS countries consists of: Armenia, Azerbaijan, Belarus, Kazakhstan, Kyrgyzstan, Republic of Moldova, Russian Federation, Tajikistan, Turkmenistan, Ukraine and Uzbekistan (United Nations, 2014). Thus, in this classification Kazakhstan is defined as economy in transition and its performance is discussed in the context of CIS not only because it is a member of this group, but for the reasons of geographic proximity and similarities in economic structure.

Dramatic transformation in former socialist countries, resulted in their reintegration into the world economy, and, in most cases, major improvements in living standards. But the way of building market economies has been difficult and long. Liberalization of trade and prices came quickly, but institutional reforms in such areas as governance, competition policy, labor markets, privatization and enterprise restructuring often faced with great difficulties (IMF, 2014a).

The banking systems of the CIS countries are currently very heterogeneous, reflecting regional and national differences. Efficiency of the processes taking place in the banking systems in the recent years has differed significantly due to the differences in the macroeconomic and political environments, as well as the policies that the governments prescribe to their national banks.

In some CIS countries, banks have become powerful national financial institutions operating both in the neighbouring countries and far abroad (Russia, Kazakhstan, Belarus, Azerbaijan), in others they are simply "digesting" small streams of cash receipts from the labour migrants and not performing the key function of transforming the national savings into investments (Kyrgyzstan, Tajikistan, Moldova, Armenia). Throughout the USSR's existence the banking system developed more or less similarly in different parts of the country; however, after its disintegration, they followed completely different paths.

Despite the fact that the banking systems of the CIS countries differ more in their development paths and efficiency indicators, they still share a number of common risks, such as:

- the shadow economy;
- high economic and industry risks;
- strong dependence on economic cycles;
- low level of well-being and significant income inequality among the population;
- underdevelopment of regulatory and legal systems;
- heterogeneity of accounting standards;
- the lack of confidence in the banking system (Trofimova, 2005).

The level of risks in the banking systems of the CIS countries is one of the highest in the world. The rapid growth of assets and loan debts, lack of information transparency, low capitalization and high concentration of business make banks unstable during the economic and political shocks and impedes their development. Despite some positive changes, CIS banks face serious potential risks, including both external shocks, and the likelihood of a shift in political course. There is an absolute need for structural reforms, consolidation and further reduction in the number of small, unviable banks. All the banks in the region have to solve numerous and difficult problems, in particular, increase the level of financial intermediation, expand the range of products, diversify the sources of income, increase efficiency, and introduce new tools and mechanisms to improve the operational quality and risk management. In order to strengthen the confidence in the banking system, it is necessary to increase the transparency of auditing and accounting, improve the information openness and quality of corporate governance, continue privatization and provide more reliable protection of the rights of investors and creditors. In addition, it is necessary to raise financial discipline and improve the efficiency of legal systems in order to improve the payment culture in different countries of the region. Without solving these problems, the CIS banks and their countries are likely to remain being the "outsiders" of the world financial system (Trofimova, 2005).

Rapid development of the banking sector was due to technical know-how and financing by foreign banks but growth became increasingly imbalanced. The resulting vulnerabilities were exposed when the global financial crisis struck, hitting the region harder than any other (IMF, 2014a).

Political and economic events of recent years had negative impact on the CIS banking sector. According to the most encouraging forecasts, the Commonwealth's banking sector will get back to its pre-crisis levels no earlier than 2019.

### 2.4 Formation of the Banking System and Impact of the Financial Crisis

The history of the formation of a market economy in the financial services sector of the country indicates that Kazakhstan had relatively well developed financial markets at the beginning of the current global financial and economic crisis. However, they were not sufficiently stable and were largely influenced by external factors.

The stages of the formation and development of the banking system of Kazakhstan will now be considered. Legislation governing "the National Bank of the Republic of Kazakhstan" stressed that: "The Republic has a two-tier banking system. The National Bank is the Central Bank and it is the top level of the banking system of the Republic of Kazakhstan" (Republic of Kazakhstan, 1995). All the other banks occupy the next level of the system as second tier banks (STB). The formation and development of the banking system can be split into five stages (Omarkhan and Konopyanova, 2011, Glass, Kenjegalieva and Weyman-Jones, 2013).

#### 2.4.1 First Stage (1988-1991)

Early development started several years prior to the formation of the banking system. By the time of independence in 1991 the banking system was represented by six Soviet banks operating as the State Bank, the Vneshekonombank, the Promstroibank, the Agroprombank, the Kredsotsbank and the Sberbank. The state-owned banks became the basis for the formation of a two-tier banking system in Kazakhstan, including the first private commercial banks. During this period monetary settlements were effected in Soviet roubles.

The first private commercial bank in the Soviet Union was opened in Kazakhstan, Shymkent city, in 1988 in the form of the "Soyuzbank". However, in 1993 as a result of a tightening of regulations the bank ceased to exist (Tretyakov, 2014)

In countries with a transition economy, and in Kazakhstan in particular, new laws on the governance of the banking system were passed in order to develop the structure of the regulatory bodies, to grant licenses to banks, to revise the system of interbank payments and staff training, and to define a possible degree of participation of foreign capital. These reforms were aimed at improving the financial stability of banks, expanding their base, increasing the availability of banking services and developing risk management systems.

### 2.4.2 Second Stage (1992-1993)

The second stage was marked by quantitative rather than qualitative growth of the banking system under conditions of high inflation.

The emerging banking system was characterized by weak legal control by the National Bank, plus lax requirements in the licensing procedure and in the minimum size of the capital base. Numerous short-lived banks were formed reaching 200 by 1993. However, more than 90% of the banks failed to fulfil the specified norms (Omarkhan and Konopyanova, 2011) and created a low degree of sustainability. In November 1993 Kazakhstan left the Russian currency zone, withdrew the Soviet Rouble from circulation and introduced the Tenge as its national currency.

### 2.4.3 Third Stage (1994-2003)

This was the largest stage of duration. The National Bank toughened the requirements for opening new banks with initial share capital set at a minimum of US$500,000 and later increased to 2 billion tenge or approximately US$15.5 million, with a share capital injection in the form of cash. For the first time, prudential standards were introduced. A Development Bank owned by the state was launched in April 2001 and funded by the proceeds from the placing of a Eurobond issue (debt securities). This would allow the provision of medium and long term loans to the Republic and local governments.

The government is also the owner of the Zhilstroysberbank, which was established in 2003 to carry out banking functions focused on medium-and long-term lending for house construction. Its activities are based on a cumulative credit system where a depositor who opened a bank account and has saved up to 50% of the property value can access bank credit for the balance. For the first three years of its activities it funded more than 50 investment projects worth about $800 million with an average project duration of 9.5 years and a weighted average interest rate of 9.7% while the market interest rate ranged from 21% to 35%.

Second-tier banks followed a program to adopt the international accounting standards (IAS) in December 1996 for a further strengthening of the banking system. According to this program, all banks had until the end of 2000 to reach the international standards in terms of capital adequacy, liquidity, asset quality, management level, accounting and transfer of information (Mirzhakypova et al., 2009). During implementation of the program, the number of banks was significantly reduced at the expense of those with unstable financial positions.

By the time of the establishment of a deposit insurance system, the banking and financial system had already demonstrated its reliability although it had experienced the effects of the Russian financial crisis. Kazakhstan was one of the first countries in the CIS to receive a sovereign credit rating at a positive level. In 1999 a deposit insurance system was established to ensure the safety of people's deposits in case of a compulsory liquidation of banks involved in a system of guarantee. It was hoped that this would enhance the flow of public savings in to the banks. A special fund created in December 1999 operated a complicated scheme of deposit compensation. Deposit value was compensated fully up to 200,000 tenge (approximately US$1,667) and indemnity was calculated on a regressive scale in excess of that amount.

### 2.4.4 Fourth Stage (2004 - 2007)

The fourth stage is regarded as a period of further development of the banking system and its integration with the world financial markets. In 2004 a new regulatory body represented the interests of the state in the form of the Agency on Regulation and Supervision of Financial Markets and Financial Organizations (AFS) sharing with the National Bank of Kazakhstan some of its powers. During this period the banks had a positive influence on the economy of the country.

From October 1, 2005 the base for the calculation of minimum reserve requirements was extended and the list of reserve assets was reduced to remove excess liquidity and attract "long" term resources by the banks.

These changes have raised the minimum reserve requirements leading to the growth of reserve asset holdings of banks at the National Bank. The adoption of these measures by the National Bank was aimed at reducing the inflationary pressure in the economy.

Before the start of the crisis of 2008, the banking system was considered to be superior to that in the CIS. It was well adapted to market condition. A legislative and methodological framework had been implemented taking into account the experience of developed countries and the fundamental principles of the Basel Committee on banking supervision and regulation. Kazakh banks were among the first in the CIS to start using the international financial reporting standards (IFRS).

The development of the banking system has significantly outstripped the pace of reform in other sectors of the economy. The small domestic manufacturing market has limited the expansion of banks. As a result, domestic banks have entered external markets. On the other hand, the expansion of banks has made them more dependent on foreign capital borrowings (Omarkhan and Konopyanova, 2011).

Basic economic growth is linked to the development of manufacturing industry, real estate, construction and trade. For housing construction, investors needed large capital funds. Banks began to grant loans to firms based on the security of assets acquired without checking their creditworthiness. In 2005 the volume of bank loans increased by 74.6%, by 82.7% in 2006 and by slightly less than 54.7% in 2007. In the total volume of loans, the share of mortgage lending amounted to 37.4 %.

The growth in the financial sector of the economy in those years involved a considerable accumulation of risks in the banking system. Although there was growth of external borrowing and high rates of increase in the volume of credit secured by the quality of the loan portfolio, the potential for deterioration of asset value was not adequately evaluated by the banks.

Rapid economic development from 2000 to 2007 caused by the growth of oil prices increased confidence in all sectors of the Kazakhstan economy and in the banking sector in particular. The strong growth of external borrowing by the banks, unfortunately, was not under the rigid control of the government regulatory bodies resulting in an increase in the foreign debt of the banking sector by 79.3 times during this period. The proportion of bank debt to the total external debt of Kazakhstan was also steadily growing (Glass, Kenjegalieva and Weyman-Jones, 2013).

The expansionary lending to the construction industry and the real estate market by banks caused, on the one hand, a further increase of property prices and the enhancement of the exposure of the banking sector to credit risk. On the other hand, the construction sector became almost entirely dependent on bank financing.

The poorly diversified economy was not able to digest the huge inflow of foreign currency, caused by a large amount of cheap borrowing on the international financial markets during 2005-2007. This led to the formation of “bubbles” in the construction sector and in property asset prices in general.

One of the reasons for the failure of the regulatory bodies was, apparently, the fact that the process of raising foreign loans and loan growth became uncontrollable (Marchenko, 2008).

At the same time, an inflow of foreign capital in to the banking sector of Kazakhstan began by the opening of foreign bank subsidiaries (SB Sberbank of Kazakhstan, SB RBS Kazakhstan, SB HSBC, etc.) and by the foreign purchase and acquisition of Kazakhstan banks (UniCredit Group and ATF Bank).

Thus, 2000-2006 was a period of rapid development of the economy of Kazakhstan.

### 2.4.5 Fifth Stage (2008 to the present day)

The fifth stage is characterised as a period of crisis in the financial system of Kazakhstan as part of the global financial turmoil and the need to overcome its consequences. With the onset of the global financial crisis the leading banks of Kazakhstan underwent severe tests.

With the growth of the US mortgage crisis there was a threat of economic recession, and foreign holders of Kazakh bank securities began to sell and withdraw their funds from Kazakhstan. The credit boom in Kazakhstan lasted longer than was typically the case of credit bubbles. The first reason for the local credit crisis was the moral hazard problem, because too many risky loans were issued in the credit boom, especially mortgages. The 'moral hazard' hypothesis is the problem of excessive risk-taking when banks with relatively low capital respond to incentives by increasing the riskiness of their loan portfolio, which leads to higher nonperforming loans on average in the future. The presence of moral hazard gives an alternative explanation for nonperforming loans, so the effects of measured cost efficiency on nonperforming loans could be biased if the potential effects of capital were neglected. Moral hazard effects can magnify the effects of other problems mentioned by Berger and DeYoung (1997) relating to periods of bad luck, bad management, skimping. Any of those issues could be the primary cause of reduced capital and moral hazard incentives. Kazakh banks were heavily dependent on external finance and they were unable to recover their external debts and to service their considerable liabilities (Glass, Kenjegalieva and Weyman-Jones, 2013).

This decline in bank funding resulted in lower activity in the construction and other industries.

The following factors had contributed to the bank credit boom in Kazakhstan:

1. The creation of conditions by the government for provision of mortgage loans to citizens on favourable conditions to relieve a housing shortage;
2. The demand for housing;
3. The lag of supply behind demand led to a speculative rise in housing and real estate prices;
4. The rise in house prices led to massive purchases of housing for speculative purposes;
5. The decline in interest rate and the share of initial payments on mortgage loans.

The analysis of the stages of the banking development through reliance on external borrowing by banks leads to the conclusion that banks in the country acted as "get rich quick" institutions by the generation of short term excess profits from speculative trading in financial markets (Glass, Kenjegalieva and Weyman-Jones, 2013).

The concentration of bank lending during this period in the individual segments of construction, trade and consumer loans led to a growth of credit default risk.

To illustrate, the short-term loans of STB accessed in the capital market at an interest rate of approximately 4-5% per annum were invested in the domestic economy in the form of lending to small and medium-sized businesses. Due to the increase in housing and social building construction, preference was given to loans working capital to construction companies at 10-12% rates of interest and to mortgage lending to the public at 12-17%. Thus, the bank's net profit margin according to a minimal estimate was approximately 5-7% per annum. The ease and speed of obtaining such returns on capital contributed to a sharp increase in the volumes of foreign short-term borrowing by second-tier banks to fund new loans. The profit margin was not utilised by the banks to increase their liquidity but was directed to extending further credit to the real estate sector.

The funding scheme was very favourable for banks and construction companies, although, as the analysis shows, it carried certain signs of a "financial pyramid". As a result, the gross external debt of the country reached a critical level of over 100% of the GDP (Baimuratov, 2010).

The situation in the world financial markets deteriorated and strongly affected the mortgage lending sector of the country. Therefore, in the third quarter of 2007 compared to the previous quarter, there was a decrease of 34% in the volume of credit extended to citizens for the construction and purchase of housing.

Banks faced an increase in their financing cost in the world markets and introduced new credit terms under which loans were granted with great care at higher rates and on conditions that were more stringent. Due to the lack of liquidity, the interest rate on mortgage loans rose in at least 2%. With the inclusion of all payments for loan servicing and fees, borrowing costs rose considerably, leading to a drop in demand for bank loans, especially for mortgages. Due to the emergency measures of the National Bank and the government, the crisis shocks were overcome.

The government had timely taken a decision to support the financial sector through the allocation of funds from the National Fund of US$3,240 million and investing in the capital of the four core banks to achieve a 25% of Kazkommertsbank ownership, 25% of Halyk Bank ownership, 78.14% of BTA Bank ownership and 76% ownership of Alliance Bank.

A restructuring of the debts of BTA Bank, Alliance Bank and Temirbank was conducted. As a result, bank loans of US$11,000 million were written off (National Bank, 2010). The above three banks began the process of restructuring in the spring of 2009.

In addition, about US$1,000 million were allocated to the banks for lending to the real economy, thereby financing 71 major borrowers and supporting more than 43,000 jobs (Damu, 2014).

Speaking at the Forum on Financing Growth in Kazakhstan Kelimbetov the Chairman of the National Bank said that the anti-crisis program of 2008-2009 cost the state 6% of GDP to support the banking sector (Kelimbetov, 2014).

Standard & Poor’s has assigned the following credit ratings for the banks that have received support from the government as part of the anti-crisis program.

**Table 2.2: Standard &Poor's Credit Ratings of Banks, 2007 and 2014**

| Bank's name | 01.01.2008 | 01.01.2009 | 01.01.2010 | 01.01.2011 |
|---|---|---|---|---|
| Kazkommertsbank | BB/Negative/B | BB/Negative/B | B/Negative/C | B/Negative/C |
| Halyk Bank | BB+/Negative/B | BB+/Negative/B | B+/Negative/B | B/Stable/B |
| Alliance Bank | B+/Negative/B | B+/Negative/B | D/D | B-/Stable/C |
| BTA Bank | BB/Negative/B | BB/Negative/B | D/D | B-/Stable/C |
| Temir bank | B+/Negative/B | B+/Negative/B | CC/Negative/C | B/Stable/B |

Continuation of Table 2.2

| Bank's name | 01.01.2012 | 01.01.2013 | 01.01.2014 |
|---|---|---|---|
| Kazkommertsbank | B+/Stable/B | B+/Negative/B | B/Stable/C |
| Halyk Bank | BB/Stable/B | BB/Stable/B | BB/Stable/B |
| Alliance Bank | B-/Stable/C | B-/Stable/C | CCC/Negative/C |
| BTA Bank | B-/Negative/C | B-/Negative/C | B-/Negative/C |
| Temir bank | B/Stable/B | B/Stable/B | B/Stable/B |

**Source:** http://www.standardandpoors.com

At the end of 2014, Standard & Poor's attached the long-term rating of "B" to Kazkommertsbank to Credit Watch with negative implications. In 2014, Kazkommertsbank announced the acquisition of 46.5% of the shares of BTA Bank and the establishment of control over the bank's operations.

Only the Kazkommertsbank and Halykbank of these five banks survive today: in 2015 BTA Bank and Kazkommertsbank merged and the Alliance Bank and Temir Bank merged with Forte Bank.

In 2008, the banking sector of Kazakhstan suffered a sharp reduction in growth, a significant deterioration of asset quality and a major decline in profitability.

In order to regulate the short-term liquidity of banks, the reserve ratio requirements for the internal liabilities of banks were reduced from 5% to 2% and for other liabilities from 7% to 3% on November 18, 2008. The new requirements allowed banks to release approximately 350 billion tenge of extra liquidity[3] (National Bank of Kazakhstan, 2009).

The National Bank and the Agency of Financial Supervision (AFS) took steps to strengthen the regulation and supervision of the management of profitability in the banking sector. Refinancing interest rates were raised and the AFS imposed more stringent prudential standards including new minimal reserve requirements (MRR) from July 1,

[3] National Bank of Kazakhstan Reports on the current state of the banking sector, www.nationalbank.kz

2009 (National Bank of Kazakhstan, 2009).

As of August 1, 2009, the share of standard loans in the loan portfolio of STB decreased to 30.6% and doubtful loans to 44.4% but non-performing loans (NPL) rose to 25%. At the beginning of 2009, NPL accounted for 4.4 per cent. The deterioration in the quality of bank credit portfolios threatened the liquidity and profitability of banks (National Bank, 2009).

On August 1, 2009, the share of the 10 largest banks in total assets of the banking sector was nearly 90% with the top 3 at 57.7%.

The main banks had the highest proportion of NPL. For example, by August 1, 2009, the highest proportion of NPL in the BTA Bank was 67.2% and was 68.9% in the Alliance Bank indicating a continuing deterioration in the asset quality of banks.

Separate minimum reserve requirement (MRR) standards were set at 0% for all bank liabilities in November 2009 to maintain the current liquidity of banks in the process of debt restructuring (The National Bank, 2009).

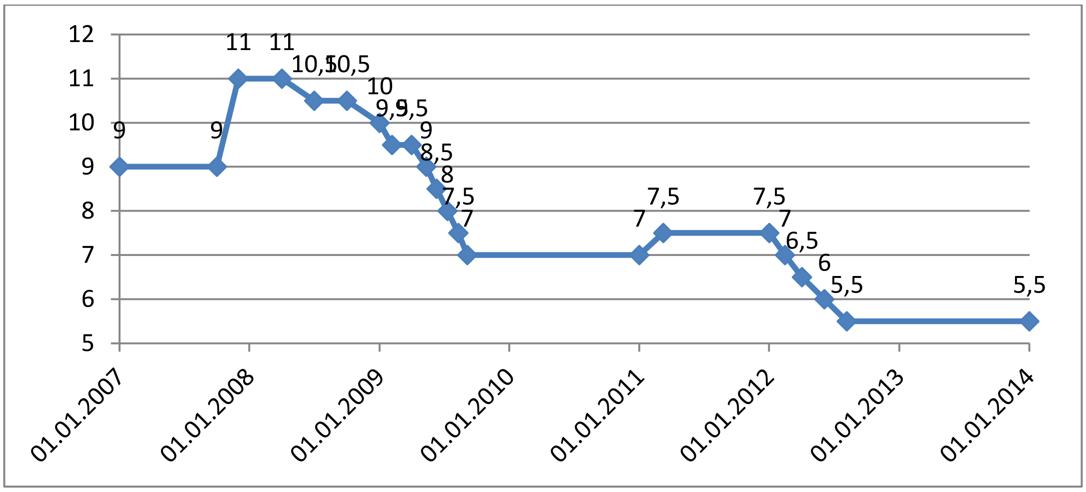
The global financial crisis showed that banks in Kazakhstan had suffered from structural anomalies in the economy and the financial sector due to the rapid growth of banks over a 7 year period. Accordingly, there were a concentration of external risks from foreign loans, internal risks from the rapid development of credit and external expansion, undeveloped corporate governance, large dollarization of bank activities, a lack of effective supervisory response and a scarcity of mechanisms to prevent future crises in the emerging system and to mitigate their consequences (Baimuratov, 2010).

For the auditing of the banking system by the AFS, a sensitivity analysis was performed to estimate the maximum influence of adverse factors on the sector. Three of the second-tier banks, namely BTA Bank, Alliance Bank and Temirbank, were found to have violated the standards of capital adequacy. Technical default was declared. Stress testing of the banking system was performed. As a whole, the results showed that, except for the above-stated three banks, the banking system was sustainable (National Bank, 2009, 2010).

In 2009-2010 bank credit activity was relatively low due to the low quality of available loan portfolios combined with conservative policies of the banks regarding the adoption of credit risk amid uncertain economic expectations. Deterioration in the quality of loan portfolios was due to two factors. On the one hand, the creditworthiness of borrowers declined and the non-payment of loans led to a deterioration in their quality. On the other hand, non-performing loans were not replaced by new standard loans (National Bank, 2011).

To overcome the negative effects of the crisis, it was also necessary to increase lending to the real sector of the economy. Under the conditions of crisis the government carried out more effective monetary policy by stimulating the development of the national economy and expanding demand and export production. Crucial to the banking system was the gradual reduction in the refinancing rate implemented by the National Bank from 11% on January 1, 2008 to 5.5% on August 1, 2012 (Figure 2.1). This had a positive impact on loan interest rates for banks (National Bank, 2014).

**Figure 2.1: Refinancing Interest Rate of the National Bank in the Crisis Period**




**Source:** National Bank

However, despite the decrease in the rate of refinancing, the reduction of the cost of credit was slow. On average, the real value of interest rates remained at 14-15%.

In 2011-2012, owing to the improvement of general economic conditions and, in particular, the financial condition of borrowers, the most significant factor in the deterioration of the bank credit portfolio was a failure to replace non-performing loans with performing credit. Thus, the observed tendency was to maintain the volume of the "running" portfolio under the system at the same level. Hence, banks tended to maintain the interest margin at an acceptable level by granting limited loans to the highest quality borrowers (National Bank, 2012).

In August 2014, a new concept in the development of the financial sector was adopted. Its main objectives were to create a competitive financial sector and to enhance its efficiency in the distribution of resources in the economy based on acceptable international standards, including those of the Organization for Economic Cooperation and Development (OECD). This was set for the period to 2030 and was part of the long-term planning within the framework of the implementation of the "Kazakhstan-2050" strategy.

### 2.5 Current State of the Banking Sector

According to the published data at year-end 2013 Kazakhstan GDP was $224.4 billion. The World Bank has included Kazakhstan in countries with above-average income per capita and ranking it 50th in its Global Competitiveness Index for 2013-2014 (Wold Economic Forum, 2013). Thus, by size of its economy, Kazakhstan has overtaken all the countries of Central Asia and the Caucasus together. Uzbekistan, Turkmenistan, Tajikistan, Kyrgyzstan, Azerbaijan, Georgia and Armenia had a cumulative GDP of $214.5 billion by 2013.

One of the main indicators which international practice has adopted to assess the level of development of a national banking system in terms of the economy is the ratio of total assets of the banks to GDP. Table 2.3 below shows the macro indicators characterizing the role of the banking sector in the economy of Kazakhstan

**Table 2.3: Banking Macroeconomic Indicators, January 1, 2006 to January 1, 2014**

| Indicator | 01.01.2006 | 01.01.2007 | 01.01.2008 | 01.01.2009 | 01.01.2010 | 01.01.2011 | 01.01.2012 | 01.01.2013 | 01.01.2014 |
|---|---|---|---|---|---|---|---|---|---|
| GDP (billion tenge) | 7 591 | 10 214 | 12 850 | 16 053 | 17 008 | 21 815 | 27 572 | 30 347 | 35 275 |
| Ratio of banks' assets to GDP, % | 59% | 87% | 91% | 74% | 68% | 55% | 59% | 46% | 44% |
| Ratio of banks' loan portfolio to GDP, % | 40% | 59% | 69% | 58% | 57% | 42% | 40% | 38% | 38% |
| Ratio of bank's customer deposits to GDP, % | 33% | 46% | 50% | 29% | 35% | 31% | 33% | 28% | 28% |

**Source:** National Bank of the Republic of Kazakhstan

As can be seen from Table 2.3, on January 1, 2008 the share of the banking sector assets to GDP in Kazakhstan amounted to 91% which roughly corresponds to the average of assets to GDP/index of the countries of Eastern and Central Europe. The global financial crisis of 2008-2009 has seriously undermined the banking sector of Kazakhstan. Unfortunately, since 2008, the proportion of bank assets in GDP has been steadily dropping from 74% in 2008 to 68% in 2009, 55% in 2010, 59% in 2011, 46% in 2012 and 44% in 2013. This is evidence of the extremely weak financial sustainability of Kazakh banks.

The remaining indicators such as the ratio of loan portfolios to GDP and the ratio of deposits to GDP also reflect this tendency. The global economic crisis has negatively affected the above indicators and as of January 1, 2014 none of the analysed indices reached the level of 2007. Moreover, since 2008 there has occurred a steady decrease in these macroeconomic indicators due to the reduction of the liquidity of banks and the higher level of non-performing loans. As of January 1, 2014 the banking sector of Kazakhstan includes 38 banks, 17 of which are banks with foreign participation, including 14 subsidiary banks (Table 2.4).

**Table 2.4: Structure of Banking Sector, 2006 to 2014**

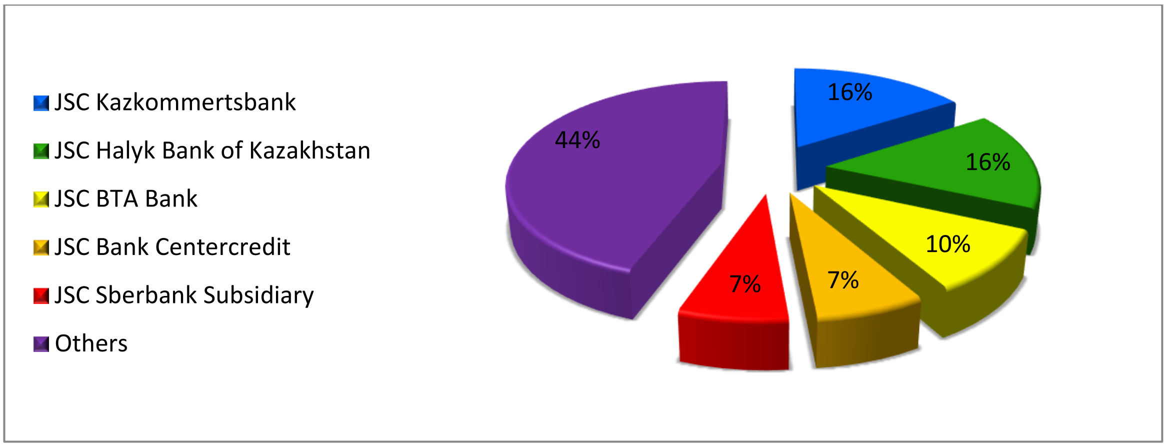
| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Number of second-tier banks | 34 | 33 | 35 | 37 | 38 | 39 | 38 | 38 | 38 |
| Banks with 100% participation of the state (Zhilstroysberbank) | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Number of second-tier bank branches | 418 | 324 | 352 | 379 | 374 | 365 | 378 | 362 | 378 |
| Number of representative offices of second-tier banks abroad | 17 | 22 | 17 | 14 | 17 | 17 | 14 | 16 | 14 |
| Number of representative offices of foreign banks in Kazakhstan | 18 | 23 | 26 | 31 | 32 | 29 | 29 | 19 | 17 |

**Source:** National Bank of the Republic of Kazakhstan

The analysis of Table 2.3 shows that the structure of the banking system has remained quite stable. Since 2008 the number of second-tier banks has remained virtually unchanged. The number of STB branches has fallen, the number of representative offices of second-tier banks abroad has declined and a significant reduction has occurred in the number of representative offices of non-resident banks in Kazakhstan from 32 in 2009 to 17 on January 1, 2014.

The number of banks with assets that exceed 1 billion tenge has increased. The share of the five largest banks of Kazkommertsbank, Halyk Bank of Kazakhstan, BTA Bank, Bank Centercredit and Sberbank was about 55% on January 1, 2014.  As of January 1, 2013, the share of the five largest banks accounted for 60 percent of all assets of the banking sector (Figure 2.2) (RFCA, 2014).

**Figure 2.2: Structure of Bank Assets, January 1, 2014**




**Source:** National Bank of the Republic of Kazakhstan

This reflects the decrease of the concentration of assets in the largest banks.

The main indicators of the banking sector and their dynamics are shown in Table 2.5. Their analysis has demonstrated that, in absolute terms, the banking system of Kazakhstan showed a negative trend (in the period from 2008 to 2014).

**Table 2.5: Main Bank Indicators, January 1, 2006 to January 1, 2014***

(billion tenge)

| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Assets | 4515 | 8169 | 9711 | 8431 | 7637 | 7424 | 7303 | 7524 | 7923 |
| Liabilities | 4073 | 7368 | 8527 | 7401 | 8285 | 6612 | 6561 | 6437 | 6858 |
| Equity | 587 | 1076 | 1184 | 1030 | -648 | 812 | 742 | 1087 | 1064 |
| Retained earnings | 71 | 93 | 180 | 8 | -1873 | 876 | 19 | -108 | 134 |
| Loan portfolio | 3062 | 5517 | 7370 | 6551 | 6370 | 5593 | 5967 | 6320 | 6839 |
| Deposits | 2523 | 4342 | 5339 | 4874 | 5154 | 4227 | 4442 | 4626 | 5045 |

*All numbers are adjusted for inflation

**Source:** National Bank of the Republic of Kazakhstan, TheGlobalEconomy.com

All indicators except retained earnings had the highest value on the 1st January, 2008. On 1st January, 2014 the assets of banks did not reach the level of 2008. From 1st January 2006 to 1st January 2008 assets grew twice from 4515 to 9711 billion tenge and then they decreased to 7303 billion tenge on 1st January 2012. Similar trends are observed in liabilities, loan portfolios and deposits. Equity had the highest value at 1184 billion tenge in 2008 and the negative value (648) billion tenge in 2010. Retained earnings had the lowest value at (108) billion tenge in 2013 and had two abnormal values on 1st January, 2010 at (1873) billion tenge and 1st January, 2011 at 876 billion tenge. All of this testifies to a transitory structure in the development of the country's banking sector characterised by the changing dynamics of key performance indicators and the negative impact of the global financial crisis.

The data on the loan portfolio of banks as one of the most important indicators of assets quality are as follows (Table 2.6).

**Table 2.6: Indicators of Loan Portfolio, January 1, 2006 to January 1, 2014 ***

(billion tenge)

| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Loan portfolio, billion tenge | 3062 | 5517 | 7370 | 6551 | 6370 | 5593 | 5967 | 6320 | 6839 |
| Customers' deposits, billion tenge | 2523 | 4342 | 5339 | 4874 | 5154 | 4227 | 4442 | 4626 | 5045 |
| Provisions | 172 | 276 | 434 | 745 | 2722 | 1731 | 1918 | 2173 | 2358 |
| NPL | 3.3% | 2.4% | 2.7% | 5.1% | 21.2% | 23% | 30.8% | 31% | 36% |

*All numbers are adjusted for inflation

**Source:** National Bank of the Republic of Kazakhstan

The total loan portfolio of banks on January 1, 2014 was 6,839 billion tenge. The banks showing an increase in the loan portfolio by January 1, 2014 are the Qazaq Banki (235.3 %), Bank RBK (119.9%) and Asia Credit Bank (88.8%). A significant portion of the total loan portfolio is in the form of NPL, the share of which by January 1, 2014 was 36%. As of January 1, 2014, the volume of provisions increased by 13.7 times and amounted to 2358 billion tenge.

Table 2.6 shows that since 2009 the level of NPL has increased dramatically. The World Bank has ranked Kazakhstan as first in the world for the volume of non-performing credits in the total number of loans granted, having reviewed the year 2012 for most economies in the world (Vorotilov, 2013). A huge value of more than 30% since 2011 made the country the undisputed world "leader" in NPL.

Shocks occurred at the turn of 2008-2009, where the level of NPL of Kazakhstan banks rose from 5.1% to 21.2%, to 23.8% in 2010, 30.8% in 2011, 31% in 2012 and 36% in

2013.

Many countries, such as Ireland, Iceland and Lithuania, have managed to reverse the economic decline in recent years, whereas the amount of NPL in Kazakhstan is growing.

The economic environment in which the financial sector operates continues to have high credit risk. The percentage of non-performing loans remains at a high level. More than 2/3 of those loans were extended by the banks in the period before 2009 during the worst of the credit crisis, showing a high "risk appetite". The potential recovery of the value of these assets remains low.

The growth rate of non-performing loans expanded in all credit sectors. However, because of the active granting of consumer loans, the share of non-performing loans in the loan portfolio of banks remained practically at the same level.

The National Bank made it compulsory for second-tier banks to provide compliance with established limits for the percentage of non-performing loans in the structure of the loan portfolio. The limit is set at 10% from January 1, 2016.

The following table shows the dynamics of the total liabilities of the banking sector of the Republic of Kazakhstan (Table 2.7).

**Table 2.7: Total Bank Liabilities, January 1, 2006 to January 1, 2014***

(billion tenge)

| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Interbank deposits | 185.1 | 237.1 | 265.9 | 226.2 | 156.6 | 132.7 | 60.7 | 87.8 | 145.0 |
| Loans received from other banks and organizations engaged in certain types of banking operations | 576.8 | 1306.7 | 1494.4 | 1028.3 | 824.4 | 338.4 | 279.9 | 142.7 | 120.5 |
| Loans received from the Government of the Republic of Kazakhstan | 3.1 | 2.0 | 6.4 | 22.7 | 31.4 | 36.0 | 41.1 | 172.3 | 166.9 |
| Loans from international financial organizations | 26.5 | 25.2 | 70.7 | 63.0 | 65.2 | 48.0 | 31.3 | 18.3 | 12.7 |
| Customers' deposits | 2532.9 | 2907.8 | 3237.0 | 3253.7 | 3967.7 | 4211.5 | 4442.6 | 4625.7 | 5044.4 |

Continuation of Table 2.7

| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Special purpose deposits of subsidiaries | 0.0 | 1433.8 | 2101.7 | 1619.9 | 1186.6 | 15.7 | 0.9 | 0.3 | 0.4 |
| Issued securities | 273.0 | 388.2 | 388.6 | 266.0 | 864.1 | 973.2 | 853.5 | 540.2 | 501.2 |
| "Repo" transactions with securities | 163.5 | 488.0 | 203.9 | 190.8 | 353.4 | 356.2 | 283.2 | 346.9 | 412.1 |
| Other liabilities | 312.5 | 579.0 | 757.6 | 730.1 | 835.6 | 500.0 | 567.3 | 503.0 | 454.7 |
| Total liabilities | 4073.4 | 7368.0 | 8526.2 | 7400.8 | 8284.9 | 6611.7 | 6560.5 | 6437.3 | 6857.8 |

*All numbers are adjusted for inflation

**Source:** National Bank of the Republic of Kazakhstan

The growth of the deposit base and reorientation of second tier banks to replenish their resources by attracting customer deposits is one of the positive aspects of the banking sector by January 1, 2014. The deposits of companies and personal customers have increased and amount to 5044.4 billion tenge.

Table 2.8 lists the main indicators regarding the profitability of the banking sector in the period from January 1, 2006 to January 1, 2014.

**Table 2.8: Profitability of the Banking Sector, January 1, 2006 to January 1, 2014***

(billion tenge)

| Indicator | 01.01. 2006 | 01.01. 2007 | 01.01. 2008 | 01.01. 2009 | 01.01. 2010 | 01.01. 2011 | 01.01. 2012 | 01.01. 2013 | 01.01. 2014 |
|---|---|---|---|---|---|---|---|---|---|
| Interest income | 342.1 | 571.0 | 1033.3 | 1035.2 | 855.4 | 644.1 | 590.5 | 588.3 | 679.7 |
| Interest expenses | 180.1 | 310.5 | 545.3 | 559.7 | 564.2 | 454.9 | 361.4 | 331.9 | 325.8 |
| Net Interest income | 162.0 | 260.5 | 488.1 | 475.5 | 291.2 | 189.2 | 229.1 | 256.4 | 353.9 |
| Non- interest income | 151.1 | 264.5 | 457.5 | 1043.1 | 3819.2 | 3296.5 | 1953.8 | 2263.0 | 1515.7 |
| Non- interest expenses | 229.8 | 407.5 | 727.7 | 1499.4 | 5974.5 | 2608.8 | 2188.4 | 2383.0 | 1711.9 |
| Net non-interest income/loss | -78.7 | -142.9 | -270.3 | -456.3 | -2155.4 | 687.7 | 234.7 | -120.0 | -196.2 |
| Net income/loss before income tax | 82.6 | 117.4 | 218.2 | 19.2 | -1864.2 | 876.9 | -5.6 | 136.3 | 157.7 |
| Income tax expenses | 9.3 | 23.6 | 37.9 | 11.6 | 8.8 | 0.7 | 14.6 | 15.9 | 23.9 |
| Net income/loss after income tax | 73.3 | 93.8 | 180.3 | 7.6 | -1873.0 | 876.2 | -20.2 | 120.4 | 133.8 |

*All numbers are adjusted for inflation

**Source:** National Bank of the Republic of Kazakhstan

The Financial Supervision Agency (FSA) published a survey on the current state of the banking sector on the website of the National Bank in 2009. It shows that the net loss of the banking sector amounted to 1,873 billion tenge due to a sharp deterioration in the financial condition of the three Kazakh banks of BTA Bank, Alliance Bank and Temir Bank. In the course of the restructuring of 2009-2010, the net income amounted to 876 billion tenge (National Bank of the Republic of Kazakhstan, 2010a, 2011a). In the last two years, the net income amounted to 120.4 billion tenge on January 1, 2013 and 133,8 billion tenge on January 1, 2014, respectively.

Some of the key problems of the banking sector of Kazakhstan for the analyzed period are as follows:

- increase in non-performing loans;
- relatively low credit activity of banks; and
- slow growth in the quality of bank loan portfolio.

Kazakhstan did not avoid the financial crisis and it seriously undermined its financial markets and economic growth. Although the country was able to recover substantially from the downturn in the economy (in the financial services sector) traces remained in the form of a high percentage of non-performing loans.

The crisis has helped banks to realize the importance of the need to reconcile business development with the objectives of risk management so as not to take on excessive risk exposure. The crisis has accelerated the process of amending the principles and regulations of bank supervision.

### 2.6 Regulation of Banking System

The regulation of the banking sector has significantly developed during more than 20 years of independence. The modern system of bank regulation and supervision was developed after the collapse of the Soviet Union. Therefore, the establishment of regulatory bodies and mechanisms is closely linked with the development of Kazakhstan's economy and banking sector.

In the post-crisis period in 2009, the main factors conditioning the stability of the financial sector were the danger of slowing economic growth in Kazakhstan and the importance of maintaining confidence in the financial system. The complexity of the joint actions of the government and the National Bank was aimed at the implementation of basic tasks to minimize systemic risks in the banking sector and the maintenance of provisions at an adequate level in order to ensure the stability of the banking system.

In case of an improvement of a bank's financial condition, the government takes measures to realize the acquired shares of a bank. This mechanism has been introduced in order to protect the interests of creditors of financial institutions, to ensure soundness of the financial system and to prevent the occurrence and deepening of systemic risk.

**Table 2.9: Regulatory Changes in Kazakhstan Banking System**

| Act/Regulatory Change | Date | Expected Impact |
|---|---|---|
| 1 | 2 | 3 |
| Law on banks and banking activity in the Kazakh Soviet Socialist Republic | June, 1991 | Establishment of the independent banking system of Kazakh Soviet Socialist Republic |
| Law on the National Bank of the Republic of Kazakhstan | April, 1993 | National Bank of the Kazakh SSR was renamed to Kazakhstan National Bank of the Republic of Kazakhstan. |
| Law on banks in the Republic of Kazakstan | April, 1993 | Defined the principles of construction and functioning of the banking system of the Republic of Kazakhstan, the legal framework of the banking operations, the rights and responsibilities of banks, relationship between banks and with the National Bank of the Republic of Kazakhstan, and also provides legal protection of depositors and creditors rights. |
| Law on the introduction of the national currency of the Republic of Kazakhstan" | November, 1993 | Kazakhstan left the Russian currency zone and introduced the Tenge as its national currency |
| Programme for the Reform of the Banking Sector | February 1995 | (i) adoption of regulations establishing independence of the NBK; (ii) adoption of BIS guidelines for prudential supervision; (iii) the introduction of on-site examinations; (iv) compulsory risk classification of assets and provisioning requirements; and (v) closure of nonviable banks |
| Law on the National Bank of the Republic of Kazakhstan | March, 1995 | Defined aims, functions, legal status and place in the banking system and the relationship with the public authorities of the Republic of Kazakhstan. Lending of the economy shifted from the National Bank to the second-tier banks. |
| Law on banks and banking activity in the Republic of Kazakhstan | August, 1995 | Defined the structure of banking system, established the basis of legislative regulation of banking system |
| Transition to International Accounting Standards | From 1994 to 2002 | Translation of Financial Statements of Kazakhstan Banks to IAS, improvement of transparency and reliability of financial reports |

**Source:** Author

Continuation of Table 2.9

| 1 | 2 | 3 |
|---|---|---|
| Law on the creation of the Guarantee (insurance) Fund of Deposits of individuals | November 1999 | Establishment of a deposit insurance system to increase confidence in the financial institutions and to protect the interests of depositors (individuals) and second-tier banks in the event of compulsory liquidation of the bank |
| Law on minimum reserve capital of second-tier banks | February, 2000 | In order to cover losses related to the implementation of banking activities, banks are required to form reserve capital from the net income before payment of dividends on ordinary shares. |
| Law on the minimal size equity of second tier banks | June, 2001 | Establishment of the requirements to the minimal size of equity of second tier banks for strengthening the financial stability of banking sector |
| Law on State Regulation and Supervision of Financial Market and Financial Organizations | July 2003 | Ensuring the financial stability of financial market and financial organizations and maintaining confidence in the financial system as a whole |
| Agency on Regulation and Supervision of Financial Markets and Financial Organizations (AFS) | December , 2003 | Agency on Regulation and Supervision of Financial Markets and Financial Organizations (AFS) separated from the National Bank to improve bank supervision and monitoring |
| Law on Credit Bureaus and Formation of Credit Histories in the Republic of Kazakhstan | July, 2004 | It applies to the introduction of compulsory requirements for banks to provide information to the Credit Bureau on their issued guarantees, securities and other contingent and potential liabilities |
| Changes in law to increase of the minimal size equity of second tier banks | October, 2004 | To increase the financial stability of second tier banks |
| Instruction on standard values and methods of calculation of prudential standards for second tier banks | October, 2005 | Supporting capitalization, liquidity, savings, monetary resources of banks and their financial sustainability. |
| Changes in law to increasing the size of minimum reserve capital of second-tier banks | May, 2008 | According to preliminary estimates, the aggregate reserve capital after implementation of the resolution will increase by 3 times and will have a positive impact on the Tier I capital |
| Law on the Amendments and Additions to Certain Legislative Acts of the Republic of Kazakhstan on the Stability of Financial System | October, 2008 | Development of tools and methods for preventive risk identification in the financial system. Strengthening the approaches of the National Bank to preventive supervision. In particular, one of the innovations of the Law on Financial Stability is the introduction of a mechanism for the rapid recovery of troubled banks.<br>Violation of prudential regulations and (or) other mandatory standards and limits. |

**Source:** Author

Continuation of Table 2.9

| 1 | 2 | 3 |
|---|---|---|
| Plan of joint actions of the Government, National Bank and the AFS to stabilize the economy and financial sector for 2009-2010 | November, 2008 | Defined a set of measures aimed at mitigating the adverse effects of the global crisis on the socio-economic situation in Kazakhstan and provided the necessary foundation for future qualitative economic growth. For this programme were allocated $10 billion aimed at: ensuring financial sector stability, stabilization of the real estate market, SME support, rapid development of agro-industrial complex and the implementation of innovative, industrial projects. |
| Law on further improvement of the system of state regulation of the financial market of the Republic of Kazakhstan | April, 2011 | Abolished the Agency for Regulation and Supervision of Financial Market and Financial Organizations (AFS), its functions were transferred to the National Bank of the country. |
| Law on amendments and additions to some legislative acts of Kazakhstan on regulation of banking and financial institutions in terms of risk minimization | December, 2011 | Involved three mechanisms of recovery of the banking system: establishment of the Fund for Distressed Assets; provide a tax deduction for problem loans; create companies to acquire distressed assets. |
| The Fund for Distressed Assets establishment | January, 2012 | Redemption of the value of bad and doubtful assets without real estate collateral from second-tier banks, for which there were created 100% or 50% provisions respectively |
| The Rules on the Use of Early Response Measures and Method of Defining the Factors Affecting the Deterioration of Financial Staten of Second-Tier Bank | April, 2014 | Established mechanisms to proactively identify risks in the financial system |
| Concept of development of the financial sector of the Republic of Kazakhstan till 2030 | August, 2014 | Increase in the efficiency of the financial sector in the redistribution of financial resources. Including the maintenance of the stability of the financial system reducing society's costs and in case of potential shocks and support of balanced economic conditions, as well as reduced credit risk in the economy. |
| Law on the factors affecting the deterioration of the financial situation of the bank and rules of application of early responses measures | February 2016 | Established the factors affecting the deterioration of the financial situation of the bank and bank conglomerate and rules of application of early responses measures and methods for determining the factors affecting the deterioration of the financial situation of the bank and bank conglomerate |

**Source:** Author

Continuation of Table 2.9

| 1 | 2 | 3 |
|---|---|---|
| Law on the normative values and methods of calculation of prudential standards | 30 мая 2016 | Established new normative values of prudential standards, the size of the bank's capital, open currency position of the bank limits and rules of calculation |

**Source:** Author

A new model of development of the banking sector focuses on strengthening the main banks and a large group of medium-sized banks. Major Kazakh banks would represent a core of the country's banking sector in the financial markets of the Eurasian Economic Union (EAEU), while medium-sized banks would provide a higher level of competition for the main banking services offered to the corporate sector and the public. For a strengthening and natural consolidation of the banking sector the National Bank from January 1, 2016 will increase gradually the minimum equity of banks from the current 10 billion tenge ($ 1 = 183. 5 tenge) to 100 billion tenge. Banks that do not meet this requirement will continue functioning but will be limited in the maximum amount of deposits of private sector that they can attract. For increasing the share of lending to GDP, an expansion of consumer financial services and the development of new high-technology services including mobile and internet banking services will be encouraged and banks will require a high level of capital for additional investments.

By 2020, it is planned to achieve the following targets:

- Assets of banks will be at least 80% of the non-oil GDP and the loan portfolio will be not less than 60% of the non-oil GDP by the expansion of their participation in financing economic growth, especially in government development programs.
- The share of Islamic banks will amount to 3-5% of the total assets of the banking system.

The macroeconomic environment in which the banks operate affect financial sustainability through the legal restrictions set by the National Bank and the government for the financial state of the competitive environment of borrowers. The internal environment of banks must counteract the challenges of the macroeconomic environment.

There is a need to maximize the approximation of regulatory practice to international standards to ensure the competitiveness of the financial sector in the context of the integration processes. In 2012, legislation changes were made in taxation pertaining to the procedure of attributing provisions formed at the request of the regulator to income deductions. From 2013, banks shall deduct only the costs incurred for the creation of provisions for IFRS.

The gradual introduction of Basel international standards is required to improve the stability of the financial system in the effective absorption of shocks. Banks need time to adapt to the new requirements.

### 2.6.1 Basel Agreements and Banking

The implementation of the Basel Accords in Kazakhstan began in the first half of 1994. The economic standards established by the National Bank for banks of the Republic of Kazakhstan were aligned with the recommendations of the international financial organizations and Basel I. As a result, the Program for Reforming the Banking System of Kazakhstan (Republic of Kazakhstan, 1995b) and the Law “On banks and banking activity in the Republic of Kazakhstan" were accepted in 1995. (Republic of Kazakhstan, 1995a).

In 2000, according to the IMF and its framework of the Financial System Stability Assessment, it was concluded that from a legal perspective the banking system of Kazakhstan fully in line with Basel I (IMF, 2004). At the forum of the American Chamber of Commerce for Economic Policy "The reform of banking regulation for Kazakhstan: creating stability in a turbulent environment" in 2011 the Chairman of the National Republic of Kazakhstan, Grigory Marchenko, said that Basel II in Kazakhstan was not implemented, because it was decided that they did not fit the conditions of Kazakhstan, and announced that the implementation of Basel III would begin in 2013 (Zakon.kz, 2011).

The introduction of Basel III standards requires conceptual changes in the existing regulatory framework on capital requirements and that in turn calls for a gradual transfer to the new requirements. Therefore, in 2012, a schedule for imposing new requirements was developed and agreed with the banks. The schedule covers the transition period similar to the 2013 -19 period of the Basel Committee on Banking Supervision and is divided into two stages. The first is the deletion of instruments that may not be part of capital in accordance with the requirements of Basel III and the second stage is a gradual increase of requirements for capital. As a result, in order to increase equity capital, banks will be given time to replace the instruments to be excluded from the capital base such as preferred shares and perpetual financial instruments or for the accumulation of profit.

The requirements of the National Bank in some areas correspond to Basel III but others should be adjusted. The comparative analysis of equity requirements is listed in Appendix

2A. The requirements for capital adequacy specified by Basel III (Appendix 2B and Appendix 2C) also differ.

Prior to the revision of national prudential standards for compliance with Basel III to tighten the adequacy ratios 1-1 and 1-2 the percentage to the values specified in the Appendix 2B were raised. With the introduction of the plan for the harmonization with the Basel III rules, these changes have been reversed.

Since the adequacy ratios are calculated by weighting assets according to their riskiness, it is also advisable to consider and reconcile these requirements (Appendix 2D).

However, the introduction of new standards that were to start on January 1, 2013, was delayed by the National Bank as well as by the banks around the world as they were not ready for the tougher requirements. Two years of delay provided for the correction of mistakes and have yielded, on the whole, positive results (Republic of Kazakhstan, 2014).

At the beginning of March 2015, the Basel Committee on Banking Supervision informed all major banks which were of significance in the global financial sector that now they must meet the new standards for tier 1 capital adequacy (BCBS, 2015). Already there is a completely different situation in the financial markets concerning risk weighting.

In 2015, Kazakhstan announced that they began the phased transition to the Basel III system of regulation of the banking sector. The National Bank (NB) has conducted a new schedule for transition. However, on October 9, 2015, the National Bank has corrected the program of transition to Basel, delaying it until 2021 (Informburo.kz, 2015).

### 2.7 Summary

The banking system of Kazakhstan, as described above, originated in 1991 with the formation of the CIS. In the initial period up to the 2008 crisis, under the direction of the National Bank, there was established a wide network of second-tier banks, which was rapidly growing.

On January 1, 2008 the share of the banking sector assets to GDP in Kazakhstan amounted to 91% which roughly corresponds to the average of the countries of Eastern and Central Europe. The global financial crisis of 2008-2009 has seriously undermined the banking sector of Kazakhstan. Unfortunately, since 2008, the proportion of bank assets in GDP has been steadily dropping from 91% in 2007 to 74% in 2008, 68% in 2009, 55% in 2010, 59% in 2011, 46% in 2012 and 44% in 2013 with a steady GDP growth (Table 2.2).

This is evidence of the extremely weak financial sustainability of Kazakh banks.

In the wake of the global financial crisis of 2008-2009, the level of NPL of Kazakhstan banks rose from 2.7% in 2007 to 5.1% in 2008, 21.2% in 2009, to 23.8% in 2010, to 30.8% in 2011, to 31% in 2012 and to 36% in 2013.

Many countries, such as Ireland, Iceland, and Lithuania, have managed to recover from the economic decline in recent years, whereas in Kazakhstan the amount of NPL is growing.

The banking sector of Kazakhstan has experienced serious difficulties in the wake of the crisis. Thanks to the unprecedented assistance provided by the government, it has survived. The banking sector of Kazakhstan has not recovered to pre-crisis levels despite strong infusion of government capital into the equity of banks, debt restructuring and tougher standards.

The readiness of Kazakhstan banks to overcome the deterioration of global conditions in both the commodity and capital markets requires an examination of the existing methods and the development of new approaches to reduce the sensitivity of banks to crisis events.

# CHAPTER 3 ASSESSMENT OF FINANCIAL SOUNDNESS OF KAZAKHSTAN BANKING SECTOR USING CLUSTER ANALYSIS


## ABSTRACT

**Purpose** – The financial systems of the majority of developing countries still feel the devastating effect of the 2008 crisis, which created a massive disaster for the global economy. Banking sectors need appropriate quantitative techniques to assess the financial soundness, strengths and weaknesses of the overall sector. The purpose of this study is to investigate the financial soundness of the Kazakh banking sector by applying cluster analysis in combination with principal component analysis to identify and group banks by the extent of their financial soundness.

**Design/Methodology/Approach** – A cluster analysis, in combination with principal component analysis (PCA), was utilized as a classification technique which uses financial ratios to recognize and group sound and unsound banks in Kazakhstan's banking sector. Cluster analysis was run on a sample of 34 commercial banks on 1st January, 2008 and 37 commercial banks on 1st January, 2014 to test the ability of this technique to detect unsound banks before they fail. For classification purpose a set of 15 financial ratios were selected as variables.

**Findings** – Key prior studies on bank soundness, distress, failure and bankruptcy were examined. Fifteen financial ratios were selected as indicators for the assessment of bank financial soundness. PCA was used as a preliminary step which reduced the number of variables in to five combined principal components. Based on these components a cluster analysis was carried out and groups of sound, risky and unsound banks were obtained. The empirical results indicate that cluster analysis is able to identify the structure of the Kazakh banking sector by the degree of financial soundness.

**Practical Implications** – The results of this study are of interest to supervisory and regulatory bodies.It is suggested that they use a cluster based methodology as a reliable and effective tool to assess the financial soundness of the banking sector. Also in this context, the methodology developed in this study can be used by bank managers, depositors and other decision makers to recognize vulnerable banks before they fail.

**Originality/Value** – This study is the first to employ a cluster-based methodology to assess the financial soundness of the Kazakh banking sector. This methodology can be used at a macro level to determine the structure of a banking sector. Also it can be used to monitor any changes in the structure of a banking sector and provide early warning

signals about the financial health of banks.

**Importance** - Assessing the financial soundness of the banking system in Kazakhstan is of particular importance as the World Bank has ranked Kazakhstan as the first in the world for the volume of non-performing credits in the total number of loans granted, having reviewed the year 2012 for most economies in the world (Vorotilov, 2013).

### 3.1 Introduction

The financial crisis of 2008 and its consequences are still creating massive costs for countries around the world. An analysis of the Kazakhstan banking sector carried out in Chapter 2 showed steady deterioration in the financial health of banks since 2008. Therefore, early prediction of financial crisis in the banking sector is urgently needed more than ever before. In this context, the current study investigates the financial soundness of the Kazakh banking sector in two steps. Firstly, it identifies the financial indicators that influence the financial soundness of banks. Secondly, it classifies banks into sound and unsound groups. The purpose is to provide early warning signs about the deterioration in the financial soundness of the banking sector. The findings of this study can help regulatory bodies to manage and supervise banks more effectively and reduce the possibility of bank bankruptcy.

As a result of the recent problems in the financial sector, bank regulators and financial market participants need a reliable and simple tool to assess the financial soundness of banks. Financial soundness has a profound influence on an entire banking system and individual banks. There is, however, no uniform definition of bank financial soundness in the literature. In general, financial soundness can be defined as a quantitative and qualitative condition of bank equity, assets and liabilities which provides a strengthening of the reliability and stability of bank activity, assuring increased confidence.

This chapter examines the financial soundness of the Kazakhstan banking sector and analyses its structure using a combination of principal component analysis (PCA) [4] and cluster analysis. The research sample consists of all Kazakhstan banks of 34 on 1st January, 2008 and 37 on 1st January, 2014. The former date represents the pre-crisis period. Based on the official governmental announcements the crisis in Kazakhstan took place between 2008 and 2009, costing the country about US $ 20 billion which is 6% of GDP to fund the anti-crisis programme (Kelimbetov, 2014). Glass et al. (2013) examined the entire Kazakh banking industry from March 2007 to December 2010 and suggested that 2010 can be chosen as the post crisis date. However, the analysis of the key financial indicators presented in Chapter 2 for the period 2007 – 2014 clearly demonstrates that the Kazakhstan banking sector still suffers from the consequences of the crisis. This was supported by the IMF's (2014) report, which stated that the financial soundness indicators

[4] Principal Component Analysis (PCA) *"is closely related to factor analysis. It is used to reduce the large number of variables into smaller number of principal components that will account for most of the variance in the observed variables. In this method, the factor explaining the maximum variance is extracted first"* (Verma, 2013; p.359).

(FSIs) showed longstanding bank weaknesses connected with inadequate underwriting standards, low asset quality and low profitability. Taking into account all of the reasons mentioned above, the researcher decided to use 1st January, 2014 as the final most recent date for the fully available data. Data were collected from reports of the National Bank of Kazakhstan and manually from the annual financial reports of all commercial Kazakhstan banks. Zhilstroysberbank was excluded as it has 100% government equity and specializes in mortgage lending, giving abnormal values of financial ratios.

Grouping sound and unsound banks can be performed by statistical techniques such as cluster analysis. Based on this concept a methodology for the assessment of bank financial soundness was developed. The effectiveness of this methodology was tested on a sample of Kazakhstan banks to see whether it could classify sound and unsound banks into discrete groups. Based on the literature review of prior studies, fifteen variables were selected from the financial reports. Then, a cluster-based methodology was employed to identify the degree of bank financial soundness and classify them into three groups of *sound, risky* and *unsound* banks.

The rest of this chapter is divided into seven sections: Section 2 presents the literature review on the assessment of bank financial soundness. Section 3 describes the methodological issues pertaining to indicator selection, data collection and the cluster based technique of assessment of financial soundness proposed in the study. Sections 4-7 present the descriptive, normative, and the empirical results of the principal component and cluster analyses and the interpretation of the results. Finally, Section 8 concludes the study.

### 3.2 Literature Review

This section will discuss the definition of financial soundness and existing assessment techniques of financial soundness related to the banking sector in order to select a relevant meaning that satisfies the purpose of this study.

#### 3.2.1 Definition of Financial Soundness

“Soundness” is derived from “sound” that means “capable of continuing for a long time at the same level”[5].

According to the Cambridge Dictionary of English, the definition of soundness is noted as a “good condition - the fact of being in good condition” and as a “good judgment - the

[5] McMillan online dictionary, http://www.macmillandictionary.com/

quality of having good judgment"[6].

In general, the concept of soundness is used primarily to refer to an organization's ability to function normally and resist various unavoidable implications from external and internal effects.

The banking legislation of Kazakhstan uses the terms "stability of financial system" (the Law "On the National Bank of the Republic of Kazakhstan", Article 2-1), and "financial stability of the bank" (the Law "On Banks and Bank Activity", Article 41). The legislator has not disclosed the content of these terms but, from the context of the law, it is clear that the term 'financial soundness' is applied to banks and "stability" has a somewhat different meaning in that part of the term referring to the banking sector as a whole.

In early 2000, the International Monetary Fund (IMF) initiated the Financial Soundness Indicators (FSI) program to define a set of financial indicators to promote cross-country comparability of such data, as well as to assist compilers and users of FSI data. In 2006, the IMF published its Compilation Guide on Financial Soundness Indicators to provide guidance on the concepts, definitions, sources and techniques for the compilation and dissemination of financial soundness indicators. Unfortunately, this guide did not provide a definition of the concept of financial soundness. Čihák (2007) complained about the abundance of definitions of financial soundness in the literature and the absence of a commonly accepted form in the IMF (2006) guide. Čihák (2007) defined financial stability as an absence of system-wide episodes when the financial system fails to function and the resistance of financial systems to stress.

The Asia Development Bank (ADB) notes that "*financial soundness is important for financial stability, and monitoring the soundness of financial institutions will help detect any possible buildup of systemic risk that could lead to a crisis*" (ADB, 2015; p.xi). ADB follows Navajas and Thegeya (2013), who developed an econometric model using macroeconomic variables and core FSIs as independent variables to explain the probability of a crisis comparing three countries of Bangladesh, Georgia and Vietnam.

Soundness allows an organization to smooth out effectively negative factors in the early stages of their operation, thereby reducing their impact in the future. The concept of soundness is characterised by a long preservation of sustainability but excludes a direct increase (Pukhov, 2013).

[6] Cambridge online dictionary of English, http://dictionary.cambridge.org/

Pukhov (2013, p.13) defines bank soundness as a "*quantitative and qualitative condition of its equity, assets and liabilities, which provides a strengthening of reliability and stability of bank activity, assuring increased confidence. It is broader than the concept of solvency, with which the concept of soundness is often equated. In its turn, the concept of reliability is narrower and refers to a bank's ability to withstand all the negative factors of the market"*.

In sum, a review of prior studies shows that there is no universally agreed definition of the concept of financial soundness (Čihák, 2007). For the purpose of the current study the most appropriate definition is given above by Pukhov (2013). The importance of this definition is that it allows the detection of the stage where a bank becomes unstable long before bankruptcy. This is because indicators of financial soundness are clear predictors that help to identify early signals of deterioration in capital adequacy, asset quality and liabilities.

Consequently, financial soundness for a bank is a condition in which the indicators characterizing the capital adequacy, asset quality and liquidity, as well as its effectiveness are within certain limits. Failing to achieve these limits will transfer a bank from a sound to an unsound state. The determination of these limits is the most important stage of the process of assessment of financial soundness in banking sector. As is known, financial indicators vary continuously under the influence of external and internal factors and the political, economic, social and financial conditions of each country. Thus, the demarcation of financial soundness limits must be made individually for the banking sector of each country.

### 3.2.2 Prior Studies on Bank Financial Soundness

As mentioned above in a previous section 3.2.1 the financial soundness of banks should be assessed in terms of the stability of development, the ability to resist external and internal negative factors in the course of activities, the guaranteed safety of customer deposits of both individuals and legal entities, the timely fulfilment of obligations and the protection of the interests of shareholders.

A financial system needs appropriate tools to assess its strengths and weaknesses and this has prompted the search for indicators of financial system soundness. Barth et al. (2002) examined the relationship between bank safety and soundness and the structure of bank supervision. They used data from 70 countries across developed, emerging and transition economies to estimate statistical connections between banking performance, the structure of bank supervision, permissible banking activities, legal environments, banking market structure and macroeconomic conditions. They found that countries with multiple authorities tend to have lower bank capital ratios and higher liquidity risk. A more focused bank supervisor than a central bank might strengthen the monitoring and control of banks.

Gasbarro et al. (2002) studied the changing financial soundness of Indonesian banks during a crisis using a unique data set provided by Bank Indonesia and employing panel data regression procedures. The data consisted of five financial ratios from 52 Indonesian banks over 18 quarters from the 4th Quarter of 1993 to the 1st Quarter of 1998. Their results showed the changing importance of the CAMELS[7] components during different economic conditions in Indonesia. They also found that different CAMELS factors were important in different economic environments and the statistical significance of the coefficients was not consistent with the weightings assigned by the bank regulators. This inconsistency was most pronounced in the pre-crisis and crisis periods.

Gaganis et al. (2006) developed a multicriteria decision aid model for the classification of banks into three groups on the basis of their soundness using a sample of 894 banks from 79 countries. They used the UTilités Additives DIScriminantes (UTADIS) method through a 10-fold cross-validation procedure. Discriminant analysis and logit regressions were chosen for benchmarking purposes. Banks were assigned three groups by the Fitch credit ratings. The asset quality, capitalization, and the market where banks operate were identified as the most important criteria in bank classification. UTADIS showed higher classification accuracies than discriminant analysis and logistic regression.

IMF (2006) proposed financial soundness indicators to monitor the health and soundness of banks. Čihák and Schaeck (2007), Babihuga (2007) and Navajas and Thegeya (2013) followed IMF's paper to investigate the FSI's effectiveness in the assessment of the financial soundness of banking systems and in the prediction of systemic banking crises.

Čihák and Schaeck (2007) analyzed aggregate banking system ratios during systemic banking crises. They utilized parametric and nonparametric tests to assess the power of these ratios to discriminate between sound and unsound banking systems and also

[7] The CAMELS rating system is an aggregated assessment of the current state of a bank that appeared in 1979 in the USA under the name of the Uniform Financial Institutions Rating System (UFIRS) which reflects the five evaluation areas of capital, assets, management, earnings and liquidity for banks. In 1995 the letter S was added to reflect sensitivity to risk market (UFIRS, 1997).

estimated a duration model to investigate whether the ratios help determine the timing of a banking crisis. The dataset for their study included 13 explanatory variables for 100 countries between 1994 and 2004. The findings from their binomial logit regression model provide evidence for the benefit of utilizing bank data on the aggregate level for macroprudential analysis. Thus, they analyzed banking systems of different countries at the macro level using macroeconomic and accounting based variables.

Babihuga (2007) analyzed the relationship between selected macroeconomic and financial soundness indicators (FSIs) using a newly assembled panel dataset of FSIs for 96 countries covering the period 1998-2005. The analysis investigates key macroeconomic indicators and FSIs of capital adequacy, asset quality and profitability in Western Europe, Emerging Europe, Asia, Latin America, Middle East, Sub-Saharan Africa and other industrial countries. The study finds a relation between FSIs' fluctuation, the business cycle and the inflation rate. It is the first to analyze the determinants of aggregated FSI data. The author exploited the advantages of panel data procedures as did Gasbarro et al. (2002).

Davis and Karim (2008) assessed the effectiveness of the logit and signal extraction early warning system (EWS) in detecting banking crises on a comprehensive common dataset of 105 countries from 1979 to 2003. Macroeconomic and financial indicators were chosen as explanatory variables.The results suggest that the logit analysis is the most appropriate approach for global EWS and signal extraction for country specific EWS. Furthermore, they stressed the importance of considering the policy makers' objectives when designing predictive models and setting related thresholds since there is a sharp trade-off between correctly identifying the difference between genuine crises and false alarms. They noted that EWS are a necessary but not a sufficient tool for predicting further crisis episodes since a generalised global model cannot be a substitute for country-specific macroprudential surveillance.

Ioannidis et al. (2010) assessed the soundness of individual banks using a sample of 944 banks from 78 countries and six quantitative techniques to classify banks in to three groups. The first group includes very strong and strong banks; the second includes adequate banks, while the third group includes banks with weaknesses or serious problems. They compared models developed using financial variables only with models that incorporate additional information in relation to the regulatory environment, institutional development, and macroeconomic conditions. They also explored the development of stacked models that combine the predictions of the individual models at a higher level and they found no evidence that the optimum stacked model can outperform the optimum individual model.

Navajas and Thegeya (2013) tested the effectiveness of FSIs as harbingers of banking crises, using multivariate logit models. The analysis draws on a data set of homogeneous indicators comparable across 80 countries over the period 2005 to 2012, leveraging the IMF's FSI database. The results indicate significant correlation between some FSIs and the occurrence of systemic banking crises and suggest that some indicators are precursors to the occurrence of banking crises. By estimating a simple multivariate logit model, they demonstrated that FSIs, broad macroeconomic indicators and institutional indicators can indeed predict crisis occurrences.

Ginevicius and Podviezko (2013) evaluated financial stability and soundness of Lithuanian banks using different multi-criteria decision analysis (MCDA) methods on a sample of 8 Lithuanian banks over the period from 2007 to 2009. MCDA methods are well suited for solving such problems, especially in the cases when data is too scarce to use statistical methods. They ranked all 8 Lithuanian banks into the categories representing reliable, sufficiently reliable and relatively weak banks, using financial ratios.

Bourkhis and Nabi (2013) attempted to compare the effect of the 2007–2008 financial crisis on the soundness of Islamic banks and their conventional peers using a matched sample of 34 Islamic Banks and 34 conventional banks from 16 countries. Using the Z-score as an indicator of bank stability, their results show no significant difference in terms of the effect of the financial crisis on the soundness of Islamic and conventional banks.

Camelia and Angela (2013) examined the financial soundness of the banks operating in Bulgaria, Czech Republic and Romania as three EU member countries from Central and Eastern Europe. The study had an original dual approach, underling both their financial soundness and ability to avoid bankruptcy. The authors employed a combined quantitative analysis based on the CAMELS framework and the Z-score. They analysed the period from 2004 to 2011 to assess the impact of the the global financial crisis on the financial soundness of banks. Their study was performed at a country-level using 13 accounting based indicators for 40 commercial banks operating in Bulgaria, the Czech Republic and Romania. Their results showed that the superior ranked banks are the subsidiaries of large pan-European banking groups. In the top five ranked banks there are some local banks and the lowest rated banks are represented mostly by the smallest banks that were involved in universal banking activities. Also, the banks of these countries demonstrated a stable financial performance under the influence of the European integration process.

Kasselaki and Tagkalakis (2014) studied the links between FSIs and the financial crisis in 20 OECD countries. They focused on aggregate capital adequacy, asset quality and bank profitability indicators compiled by the IMF. They found that the soundness of the aggregate banking system, controlling for a series of macroeconomic and fiscal factors, was affected heavily in times of severe financial crisis. This reinforced the argument for a more proactive stance on the part of the regulatory and supervisory authorities of the financial sector in order to preserve financial stability. They suggested improving both the supervisory and regulatory framework of financial markets in order to contain risks stemming from the financial sector.

In sum, a review of the literature shows that prior studies on the financial soundness of banks are conducted at cross-country level (Barth et al., 2002, Čihák and Schaeck, 2007, Babihuga, 2007, Davis and Karim, 2008, Ioannidis et al., 2010, Navajas and Thegeya, 2013, Bourkhis and Nabi, 2013 and Camelia and Angela, 2013) and single-country level (Ginevicius and Podviezko, 2013 and Gasbarro et al., 2002). It is clear from this review that the majority of the studies are carried out on the cross-country level and only two on a single-country level.

Cross-country level studies use cross-country data and employ macroeconomic, market based and accounting based indicators. Some study the relationship between FSIs and selected macroeconomic indicators using assembled panel dataset (Babihuga, 2007) and test FSI's effectiveness as predictors of banking crises using multivariate logit models (Navajas and Thegeya, 2013). Others predict banking crises using logit analysis (Čihák and Schaeck, 2007 and Davis and Karim, 2008, Navajas and Thegeya, 2013) and at the same time estimating the ability of selelcted ratios to define sound and unsound banking systems. In contrast with the above studies, Gaganis et al. (2006), Ioannidis et al. (2010), Bourkhis and Nabi (2013) and Camelia and Angela (2013) assessed the financial soundness of individual banks. Gaganis et al. (2006) and Ioannidis et al. (2010) developed quantitative models for the classification of banks into three groups on the basis of their soundness as strong banks, adequate banks and banks with weaknesses and serious problems. Gaganis et al. (2006) used UTADIS, DA and logit models, while Ioannidis et al. (2010) used six quantitative models and developed stacked models that combine the predictions of the individual models. Bourkhis and Nabi (2013) studied the financial soundness of Islamic and conventional banks. They found that the divergence of Islamic banks from the traditional model makes them vulnerable to crisis. Camelia and Angela (2013) focused specifically on the ranking of Bulgarian, Czech and Romanian banks.

Studies were devoted to analyze single-country level, for example, ranked Lithuanian banks by their levels of soundness and stability (Ginevicius and Podviezko, 2013) or examined the changing financial soundness of Indonesian banks during the crisis using a set of financial indicators (Gasbarro et al., 2002). Gasbarro et al. (2002) and found that at a time of crises the relationships between financial ratios and CAMELS ratings deteriorate and only earnings adequately discriminates banks among the ratings.

This study follows the approach of Gaganis et al. (2006) and Ioannidis et al. (2010) and classifies banks into three groups. The first group contains sound banks, the second contains risky banks, while the third group contains unsound banks. However, the current study differes from Gaganis et al. (2006) and Ioannidis et al. (2010) in three important points. Firstly, both Gaganis et al. (2006) and Ioannidis et al. (2010) are cross-country studies but this study is undertaken at the single-country level. Secondly, the models developed by Gaganis et al. (2006) needed preliminary assessment of banks, and for this purpose they used individual bank credit rating by Fitch. In contrast, the proposed cluster based methodology does not require preliminary statuses or rating; rather, it defines such statuses. Thirdly, a proposed cluster based methodology is intended to monitor changes in a banking sector's structure and provides an early signal for when some banks deteriorate and are relegated from the group of sound banks to the groups of risky or unsound banks. The current research study is the first which used PCA and cluster analysis to assess the financial soundness of the Kazakhstan banking sector.

### 3.2.3 Cluster Analysis in the Banking Sector

This chapter aims to assess the financial soundness of the Kazakhstan banking sector and classify the banks into different groups based on the extent of their financial soundness. In order to achieve this aim, it is necessary to select a reliable statistical technique first. That can be done by classification tools such as data envelopment analysis (DEA), UTilite´s additives DIScriminantes (UTADIS), artificial neural network (ANN), classification and regression trees (CART), k-nearest neighbors (k-NN), ordered logistic regression (OLR), multiple discriminant analysis (MDA) (e.g., Bell, 1997, Alam et al., 2000, Gaganis et al., 2006, Ioannidis et al., 2010 and Paradi et al., 2012). Previous studies which used cluster analysis noted that it works even when there is little data and the requirements for the normalcy of the distribution of random variables and for other classical methods of statistical analysis are not fulfilled. Shuai et.al (2013; p.461) demonstrated that "*Cluster analysis can be applied even when no performance result is available while logistic is characterised as simple result, small burden and propounding classification performance*".

Cecchetti, Kohler & Upper (2009) found that cluster analysis groups observations into clusters by minimizing differences within clusters and maximizing differences across clusters. These authors considered the costs of 40 systemic banking crises since 1980. Wolfson (2004) stated that the clusters identification is not a quest for the least number of variables that explain a result but the common features of similar groups are. Gutierrez and Sorensen (2006) claimed that the results of cluster analysis may provide some insights into the underlying interlinkages between a set of variables that other econometric techniques would not be able to detect.

Many studies use cluster analysis in finance and in particular in the banking sector. Table 3.1 provides a summary of relevant prior studies in this area. It shows that some research was devoted to the clustering of bank clients and creditors (e.g., Şchiopu, 2010, Amin et al., 2009, Tudor, Bâra and Andrei, 2012, Mäenpää, 2006, Kaynak and Harcar, 2005). Other studies used cluster analysis in the risk management of banks or to predict the likelihood of their bankruptcy (e.g., Dao and Khanh, 2014, Penikas et al., 2011, Shuai at.al, 2013). Furthermore, the IMF widely employs cluster analysis to determine groups of large complex financial institutions with common characteristics (IMF, 2010).

**Table 3.1: Cluster Analysis in Key Prior Studies**

| Reference | The Purpose of the Study | Methods Used | Country | Number of Observations/ Time Period | Set of Variables | Results |
|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| Alarm et al. (2000) | Identification of potentially failing banks. | Cluster Analysis | USA | 248 banks, 1991 | Net income to total assets, Net loan losses to adjusted assets, Nonperforming loans to total assets, Net loan losses to total loans, Net loan losses plus provision for loan losses divided by net income. | Both the fuzzy clustering and self-organizing neural networks seek to give classification tools for identifying potentially failing banks. |
| Peresetsky et al. (2004) | Probability of default model development. | Cluster Analysis, Logit and Probit Analyses | Russia | 1569 banks, 1998 | Total assets, Bank reserves for possible losses, Loans to non-financial institutions, Government bonds, Equity, Liquid assets, Private customers' deposits and accounts, Capital assets and other non-working assets, Non-government securities, Assets, Profit before tax, Amounts owed to credit institutions, Non-working assets, Overdue loans. | Developed model modifications that took into account the structural non-homogeneity of the set of banks. Proved that the bank probability of default models can be used for an EWS. |
| Safdari, Scannell and Ohanian (2005) | Development of an alternative methodology for peer group determination. | Factor and Cluster Analyses | Republic of Armenia | 17 banks, 2001 | Total assets, Average assets, Total liabilities, Loan investments, Total capital, Time deposits of physical entities, Total time deposits of physical & legal entities, Time liabilities, Demand liabilities, Statutory fund, Securities, Loans to economy, Interbank loans. | Found that Bank Assets, measured in Weight Share (%) is the principal variable in explaining variation among the banks sampled in the study. Established cut-off points and methodically delineated peer groupings. |

**Source:** Author

Continuation of Table 3.1

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| Dardac and Boitan (2009) | Assessment of risk profile and profitability of financial institutions | Cluster Analysis | Romania | 16 credit institutions, from 2004 to 2006 | Capital and reserves to total assets, Cash holdings, Securities holdings to total assets, Loans to deposits ratio, Loans to non-financial institutions. and households to total, Operational expenses to total, Return on assets ROA, Return on equity ROE, Profit margin, computed as net profit to total income, Customers' deposits to total liabilities | Cluster analysis proves to be valuable not only for assessing homogeneous banking groups in terms of risk profile and profitability, but also it can identify groups sharing similar features of the financial intermediation activity, large and complex banking groups, as a potential source of systemic risk, or the degree of financial integration in the euro area banking industry. |
| Şchiopu (2010) | Identification of Bank Customers' Profile | Cluster Analysis, PCA | Germany | 1000 records from German banks on 9 May 2010 | Duration, Credit history, Purpose, Credit amount, Years employed, Payment rate, Personal status | Identified three groups of customer profiles using Two-Step cluster analysis as skilled customers with no bad credit history; middle class customers, unemployed, but with real estate; persons with unknown properties, mostly unemployed. |
| Penikas et al. (2011) | Modelling Risk Patterns of Russian Systemically Important Financial Institutions(SIFI) | Cluster Analysis, Copula Models | Russia | All the Russian banks, from 2004 to 2010 | 75 variables | Proposed approach to SIFIs' identification classifies the banking groups in terms of marginal risk distributions, and in terms of risk distribution copula shift moments. Five distinctive bank patterns revealed comprise two SIFIs clusters of "too risky to fail" and "too many to fail" ones. |

**Source:** Author

Continuation of Table 3.1

| 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|---|---|---|---|---|---|---|
| Abudu (2011) | Bank Failure Prediction | Cluster Analysis | USA | 326 failed banks and 324 non-failed banks, from 1989 to 2000 | Assets size, Equity to assets | Proposed the cluster based approach to bank failure prediction with improved classification accuracy. An important implication of the approach is that different clusters have different variable subsets and variables that distinguish them from banks in other clusters. |
| Paradi et al. (2012) | Identifying managerial groups in a large Canadian bank branch network | DEA and Cluster Analysis | Canada | One bank with over 1000 branches, 2004 | Sales, Service, Management, Day–day banking, Borrowing, Investments, Transactions | Proposed a new grouping approach in a DEA framework designed to identify bank branch management groups. It groups branches based on their operational similarity and eliminates the impact of efficiency levels on the identification of a branch's true operating characteristics. |
| Dao and Khanh (2014) | The ability of cluster analysis to recognize vulnerable banks, common characteristics. | Cluster and PCA | Vietnam | 33 banks, from 2005 to 2007 | ROA, ROE, Net interest margin, Net profit margin, Equity capital to assets, Net non interest margin, Noninterest income over non interest expense, Asset utilization, Reserve ratio, Operating efficiency ratio, Total loan over total deposit, Temporary investment ratio. | Found that cluster analysis helps identify the vulnerable banks in the crisis. ROA, ROE, and Equity capital to assets ratio can be the warning indicators. |

**Source:** Author

It can be seen from Table 3.1 that, in most cases, cluster analysis is used in combination with factor analysis or PCA (Safdari, Scannell and Ohanian, 2005, Şchiopu, 2010, Abudu, 2011, Dao and Khanh, 2014). For example, Safdary, Scannell and Ohanian (2005), in their study of Armenian banks, use PCA and cluster analysis to allocate 17 banks to similar groups, based on 13 accounting based indicators. Division of banks into groups is usually made to specify their position in peer groups and the calculation of peer group ratio averages. Almost all presented studies use cluster analysis to produce final results such as a recognition of vulnerable banks or an identification of potentially failing banks. Only two research studies by Abudu (2011) and Peresetsky et al. (2004) used cluster analysis as preliminary step to improve the predictive power of their models. Abudu (2011) utilised two basis of clustering by asset size and time series of failed and non-failed banks a year prior to failure. Peresetsky et al. (2004) classified banks into three clusters by giving values to a bank parameter and used expert and automatic approaches.

This study employs two statistical techniques of PCA and cluster analysis following Dao and Khanh (2014) and Safdary, Scannell and Ohanian (2005) and defines the structure of the banking sector of Kazakhstan according to the degree of a bank's financial soundness which was to similar Ioannidis et al. (2010). Banks are divided in three groups: unsound, risky and sound. This structure can be considered as the final result that gives an indication of the levels of soundness and the stability of bank activity and provides a clear picture for supervision bodies, bank managers, depositors and other decision makers. At the same time this structure can be considered as a preliminary step for determining samples of sound and unsound banks for the construction of a model to predict unsoundness.

### 3.2.4 Research Indicators

An assessment of financial soundness requires a dataset of variables that help to distinguish a group of banks with similar financial characteristics, and to identify the significant indicators for detecting sound and unsound banks. Prior studies widely employed financial ratios, plus macroeconomic, industrial and institutional variables.

In the literature, bank failure indicators can be grouped into two categories: market based measures and accounting based measures. Market based indicators rely mostly on market prices of bank equity. Accounting based measures are widely used in literature as a proxy for individual bank stability and risk of bank default. According to Chiaramonte and Poli (2014) market based measures have limited scope as – they cannot be calculated for unlisted banks. A vast majority of banks in Europe are not listed. Majority of Kazakhstan banks are not listed either.

At the same time banking failure does not happen overnight and it is usually a process that takes several years (Agarwal and Taffer, 2008), that is why accounting-based models can capture adverse performance in advance and predict failure. Another key point is that most of the debt covenants are issued based on accounting information, making the latter one of the main determinants of financial failure.

In 2016 Micha, K. tested 18 default probability regressions and  was not able to conclude that the market based risk measures are better predictors than accounting based risk measures. Further, Micha, K. (2016) considers three advantages of accounting based measures. The first advantage supports conclusions of Agarwal and Taffer (2008) that bank failure is not an unexpected event and bank default is the peak point of many years of negative performance that could be captured by accounting based risk measures. The second benefit is that the loans covenants rely on accounting information and the accounting based indicators are more likely to include information about loan covenants. The third advantage is in the double entry system. It ensures minimal effect on a measure which combines different facets of accounting information from window dressing the accounts and changes in accounting policies.

Considering all the aforesaid advantages, accounting-based measures will be employed in the current study to assess the financial soundness of the Kazakhstan banking sector and identify its structure by the extent of bank financial soundness.Various studies have proposed the use of market-based indicators of detecting turmoil in banking systems (e.g. Babihuga, 2007, Čihák and Schaeck, 2007, Demirgüç-Kunt and Detragiache, 1998, Davis and Karim, 2008, Poghosyan and Čihák, 2011, Hagendorff and Vallascas, 2011, Navajas and Thegeya, 2013). Others used financial ratios to assess the strengths and weaknesses of banks and to estimate their financial soundness (e.g., Flannery and Sorescu, 1996, Akhigbe, Madura and Martin, 2007, Agarwal and Taffler, 2008, Sinkey, 1975, Ozkan-Gunay and Ozkan, 2007, Foos, Norden and Weber, 2010, Psillaki et al., 2010, Jakubik and Tep, 2011, Chiaramonte and Casu, 2013, Othman, 2013). Table 3.2 provides a summary of relevant prior studies in this area.

**Table 3.2: Research Indicators Used in Prior Studies**

| Source | Indicators |
|---|---|
| Flannery and Sorescu (1996) | **Market-based:** Ratio of total (book) liabilities to (the market value of common stock plus the book value of preferred stock), Absolute value of the bank's maturity gap, as a proportion of equity market value.<br><br>**Accounting-based:** Ratio of nonaccrual loans to total assets, Ratio of accruing loans dou past 90 days or more to total assets, Ratio of other real estate owned ("OREO") to total assets, Ratio of annual net income to year-end total assets. |
| Babihuga (2007) | **Macroeconomic variables:** Real per capita GDP, Real interest rate, Real GDP growth, Consumer price index, Real lending rate, Real effective interest rate, Unemployment rate, Banking system claims on the private sector to GDP, Terms of trade.<br><br>**Industry variables:** BCP index, Bank deposits to GDP, Deposit money bank assets to GDP, Concentration<br><br>**FSIs:** Capital to assets, Regulatory capital to risk-weighted assets, Non performing loans to total loans, Return on assets, Return on equity. |
| Čihák and Schaeck (2007) | **Macroeconomic:** GDP growth (real), M2/international reserves, Real interest rate, Inflation, GDP per capita (real), Credit to the private sector, Credit growth (real)<br><br>**Core Set of FSIs:** Regulatory capital to risk-weighted assets, Nonperforming loans to total gross loans, Nonperforming loans net of provisions to capital, Return on equity, Capital to assets.<br><br>**Encouraged Set of FSIs:** Total debt to equity, Return on equity. |
| Akhigbe, Madura and Martin (2007) | **Market-based:** Bank Size by Natural log of the market value of equity, Growth by Market-to-book equity ratio.<br><br>**Accounting-based:** Equity to total assets, Financial leverage, Return on equity, Nonperforming loans to total assets. |
| Agarwal and Taffler (2008) | **Market-based:** Dividend rate (Total dividends / (total liabilities + market value of equity), Market value of common equity, Asset volatility, Market share, Average credit spread, Prior probability of failure, Share of defaulters, Loss given default.<br><br>**Accounting-based:** Return on assets, Return on equity, Return on debt, Return on risk weighted assets |
| Demirgüç-Kunt and Detragiache (1998)<br><br>Davis and Karim (2008) | **Macroeconomic variables:** Real GDP growth, Change in terms of trade, Nominal depreciation, Real interest rate, Inflation rate, Fiscal surplus/ GDP.<br><br>**Financial variables:** Money and quasi money **(**M2)/ Foreign exchange reserves, Credit to private sector/ GDP, Bank liquid reserves/ Total bank assets, Real domestic credit growth<br><br>**Institutional variables:** Real GDP per capita, Deposit insurance |

**Source:** Author

Continuation of table 3.2

| | |
|---|---|
| Poghosyan and Čihák (2011) | **Macroeconomic:** Market discipline, Inflation, Per capita GDP (logs), Share of domestic credit in GDP (logs).<br><br>**Market-based:** Concentration by Herfindahl Index, Deviation of stock prices from their fundamental value, Wholesale liabilities (share).<br><br>**Accounting-based:** Total equity/total assets, Loan loss provisions/Total loans, Total costs/total income, Profit before taxes/total equity, Liquid assets/total assets, Interest expenses /deposits. |
| Hagendorff and Vallascas (2011) | **Macroeconomic conditions:** Coincident index by Federal Reserve bank of Philadelphia, Governance variables, Log (CEO age), Entrenchment index, External monitoring index.<br><br>**Deal characteristics:** Deal value over market value of the acquirer, Dummy variable which is equal to 1 if the target is listed, Percentage of a deal paid for in cash.<br><br>**Acquirer characteristics:** Net income over total assets, Market value of equity over book value of equity, 1–(equity divided by total assets), Log of total assets, Market model cumulative abnormal return between −10 days to +1 day relative to the merger announcement date. |
| Navajas and Thegeya (2013) | **Macroeconomic:** GDP growth (real), Broad money/international reserves, Inflation, Credit to the private sector, Current account, Monetization, Real exchange rate, Credit default swap spread, Composite governance indicator.<br><br>**Core and Encouraged Set of FSIs:** Capital/risk weighted assets, Nonperforming loans net provisions to capital, Nonperforming loans/total loans, Return on equity (banks), Interest margin to gross income, Non-interest expenses to gross. |
| Sinkey (1975) | **Accounting-based:** (Cash + US treasury securities)/assets, Loans/assets, Provision for loan, Losses/operating expense, Loans/(capital + reserves), Operating expense/operating income, Loan revenue/total revenue, US treasury securities revenue/total revenue, State & local obligations' Revenue/total revenue, Interest paid on deposits/total revenue, Other expenses/total revenue. |
| Ozkan-Gunay and Ozkan (2007) | **Accounting-based:** Shareholders' equity, Total income/deposit, Non-deposit funds, Net working capital/total assets, Position/shareholders' equity, Non-performing loans/total loans, Permanent assets/total assets, FX assets/FX liabilities, Net income/average total assets, Net income/average shareholders' equity, Liquid assets/total assets, Liquid assets/deposit, non-deposit funds, FX liquid assets/FX liabilities, Interest income/interest expenses, Non-interest income/non-interest expenses, Interest income/average earning assets, Interest income/average, Non-interest income/total income, Interest expenses/total expenditure, Total asset per branch, Total deposit per branch, Total loan per branch. |

**Source:** Author

Continuation of table 3.2

| | |
|---|---|
| Foos, Norden and Weber (2010) | **Accounting-based:** Relative loan losses, Loan growth, Abnormal loan growth, Relative interest income, Level of capitalization, Equity-to-total assets, Total assets, Total customer loans, Loss-income ratio, Indicator of equity abnormal growth. |
| Psillaki et al. (2010) | **Accounting-based:** Working capital (current assets minus current liabilities) to total assets ratio, Working capital to equity ratio, Debt to assets, Debt to equity ratio, Sales to assets, Sales to equity ratio, Ratio of intangible assets divided by total assets, Ratio of intangible assets divided by equity. |
| Jakubik and Tep (2011) | **Accounting-based:** Current ratio, Quick ratio, Cash ratio, Working capital, Capitalization ratio, Leverage I, Leverage II, Leverage III, Debt payback period, Interest coverage, Cash-flow I, Cash-flow II, No credit interval, Retained earnings, Gross profit margin, Return on assets, Return on equity, Net profit margin, Average receivable collection period, Inventory ratio, Sales turnover, Payables ratio. |
| Chiaramonte and Casu (2013) | **Accounting-based:** Loan loss reserve/gross loans, Unreserved impaired loans/equity, TIER 1 Ratio, Leverage equity/total assets, ROA (%) = net income/average total assets, ROE (%) = net income/average equity, Net loans/deposits and short-term funding, Liquid assets/deposits and short-term funding. |
| Othman (2013) | **Accounting-based:** Shareholders' equity /total assets, Shareholders' equity / (deposits and non-deposit funds), Net working capital/total assets, Shareholders' equity/(total assets + contingencies and commitments), Financing/shareholder's equity, shareholder's equity / total financing, Loans/total assets, Non-performing loans/loans, Permanent assets/total assets, Specific provision / total financing, Liquid assets/total assets, Liquid assets/(deposits and nondeposit funds), Total deposits / total loans, Total financing / total deposits, Net income(loss)/total assets, Net income(loss)/shareholders', Equity, Net income (loss)/total share, Net income before tax/average total assets, Provision for loan losses/total assets, Net interest income after provision/average total assets, Interest income/interest expenses, Total income/total expenses, Interest income/total income, Interest expenses/total expenses, Operating expenses / total assets, Interest expenses / total deposits, Total liabilities / total equity, Total liabilities / total assets, Total assets / total equity. |

**Source:** Author

Gentry and Shen (2010) considered that accounting-based measures are calculated from financial reports and capture historical or short-term financial performance. Conversely, market-based measures indicate the price of bank shares, the value of dividends, the number of shares in issue and capture future or long-term performance.

The market-based measures were used in the work of Flannery and Sorescu (1996), Poghosyan and Čihák (2011), Hagendorff and Vallascas (2011), Agarwal and Taffler (2008).

Gavin and Hausman (1996), Hardy and Pazarbaşioğlu (1998), Demirgüç-Kunt and Detragiache (1999), and the European Central Bank (2005) use predetermined (lagged) macro variables as leading indicators and typically do not consider the institutional environment. Demirgüç-Kunt and Detragiache (1998, 2005). Hutchinson and McDill (1999), Eichengreen and Arteta (2000), Hutchinson (2002) and Babihuga (2007) take account of the institutional environment variables such as deposit insurance dummy, central bank independence, liberalisation and market based variables, inflation, credit growth, domestic credit to the private sector/GDP, GDP growth.

Čihák and Schaeck (2007) identified crisis countries to code the dependent variable following survey of systematic banking crises of Demirgüç-Kunt and Detragiache (2005) and updated database of systemic and nonsystemic banking problems since the 1970s. As independent variables Čihák and Schaeck (2007) used five core and two encouraged indicators from FSI (Table 3.2).

The accounting-based measures were used in a large number of studies (Sinkey, (1975), Gamesalingam and Kumar (2001), Rahman et al. (2004) Akhigbe, Madura and Martin (2007), Agarwal and Taffler (2008), Foos, Norden and Weber (2010); Psillaki et al. (2010); Jakubik and Tep (2011); Chiaramonte and Casu (2013) and Othman (2013). Agarwal and Taffler (2008, p.21) provide three arguments in favour of this approach. *"Corporate failure is the culmination of several years of adverse performance and, hence, will be largely captured by the firm's accounting statements. Second, the double entry system of accounting ensures that window dressing the accounts or change in accounting policies will have minimal effect on a measure that combines different facets of accounting information simultaneously. Finally, loan covenants are generally based on accounting numbers and this information is more likely to be reflected in accounting-ratio-based models".*

The informative value of accounting-based models is based on their ability to provide advance signs of an emerging crisis by detecting the symptoms of bank financial difficulties (Sinkey, 1975).

Agarwal and Taffler (2008) concluded that the accounting based approach shows significant economic benefit over the market-based approach. The market-based valuation models are conceptually more attractive. Yet, regarding the accuracy of predictions, there is little difference between the market-based and accounting models.

Chiaramonte et al. (2015) warned that market-based measures display an important limit because they cannot be computed for unlisted banks whereas, in Europe, the great majority of banks are not listed.

Accounting-based-measures are also employed in the well-known CAMELS approach as a commonly used tool for risk assessment, monitoring, early warning and prediction of bank failure (Thomson, 1991; Berger, Herring and Szegö, 1995; Gamesalingam and Kumar, 2001; Rahman et al. 2004; Oshinsky and Olin, 2006; Ozkan Gunay and Ozkan, 2007; Othman, 2013; Ioannidis et al., 2010; Poghosyan and Čihák, 2011; Vazquez and Federico, 2012; Hogan, 2014; Chiaramonte et al., 2015).

The set of CAMELS measures is used by supervisory and regulatory bodies to classify banks according to their financial soundness and provide an estimate of overall bank credibility. In the empirical literature, there is a general agreement that the accounting-based CAMELS measures can split banks according to their financial vulnerability and can predict bank distress (Othman, 2013).

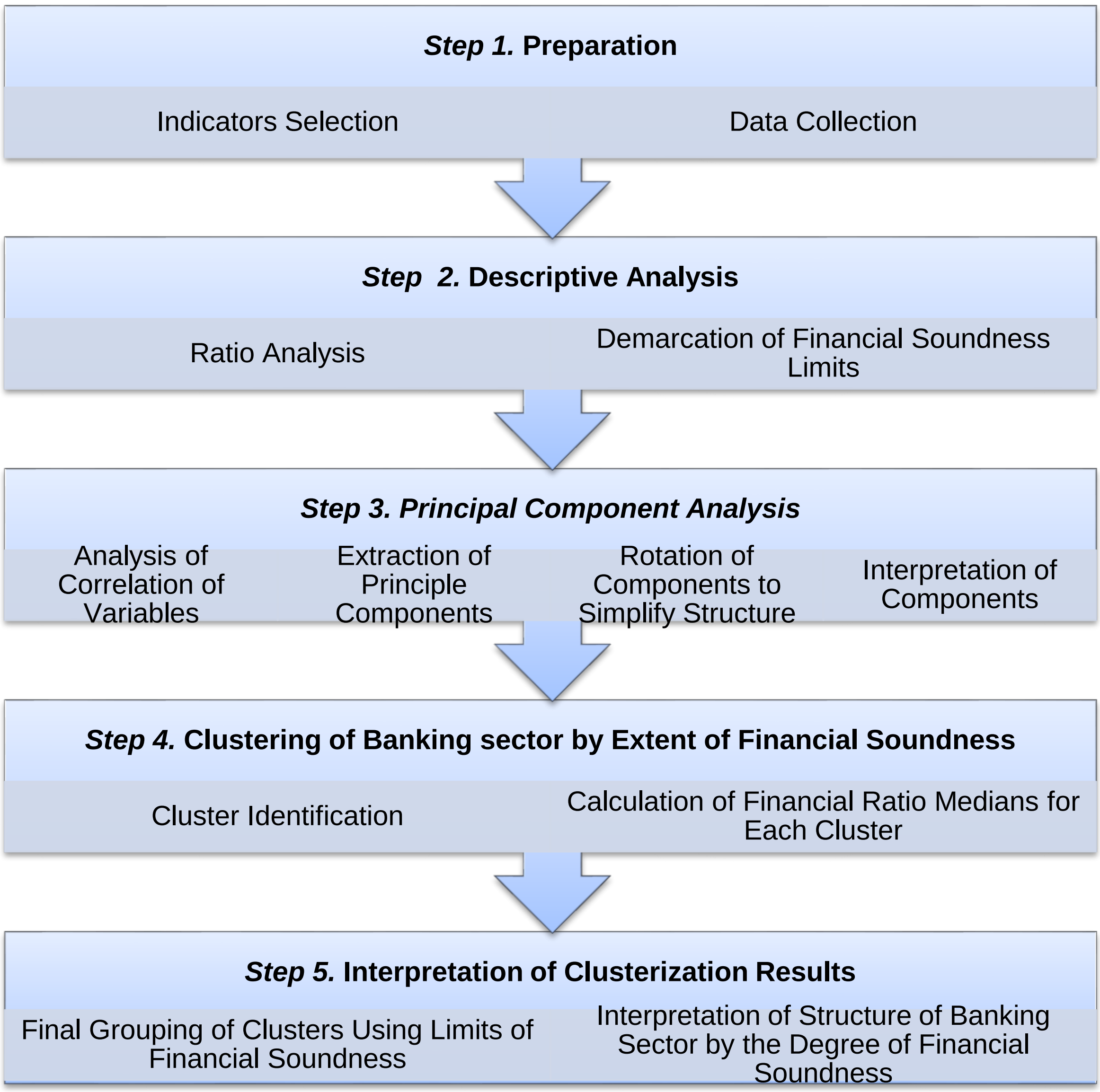
Therefore, the current study uses accounting-based indicators to assess the financial soundness of the Kazakhstan banking sector and identify its structure by the extent of bank financial soundness. These financial indicators assess the capital adequacy, assets quality, management, earnings and liquidity.

### 3.3 Cluster Based Methodology of Assessment of Financial Soundness

In line with previous research (Table 3.1) this study utilizes cluster analysis to assess the financial soundness of the Kazakhstan banking sector. In particular, cluster analysis is used to determine groups of banks where a calibrated set of selected indicators behave in similar ways and identify the structure of the banking sector by the extent of financial soundness. Specifically, this chapter seeks to answer the first research question of whether cluster analysis can identify the structure of the banking sector according to the extent of its financial soundness.

To achieve this goal the following analysis was developed in 5 stages (Figure 3.1):

**Figure 3.1: Cluster Based Methodology of Assessment of Banking Sector Financial Soundness**




**Source:** Author

### 3.3.1 Indicators Selection and Data Collection – Step 1

The first step starts from the selection of indicators which was based on a review of relevant prior studies. Following the CAMELS acronym indicators were selected to reflect the main characteristics of capital adequacy, assets quality, management, earnings and liquidity (Table 3.3). Selected financial ratios represent the five CAMELS components but the current study does not follow the CAMELS approach because its rating system is based on on-site examinations using financial ratios.

**Table 3.3: Financial Ratios Selected for Research Study**

| | Code | Ratio | Measurement | References |
|---|---|---|---|---|
| Capital Adequacy | **R1** | Capital adequacy ratio (CAR) | Equity / Total Assets | Estrella et al., 2000<br>Babihuga, 2007<br>Čihák and Schaeck, 2007<br>Akhigbe, Madura and Martin, 2007<br>Foos, Norden and Weber, 2010<br>Poghosyan and Čihák, 2011<br>Diaconu and Oanea, 2014<br>Dermine, 2015 |
| | **R2** | Regulatory capital to risk-weighted assets | Regulatory Capital / Risk-Weighted Assets | Babihuga, 2007<br>Čihák and Schaeck, 2007<br>Ravi and Pramodh, 2008<br>Chauhan et al., 2009<br>Michalak and Uhde, 2012<br>Navajas and Thegeya, 2013 |
| | **R3** | Regulatory Tier 1 capital to risk-weighted assets | Tier 1 Regulatory Capital / Risk Weighted Assets | Chauhan et al., 2009<br>Ravi and Pramodh, 2008<br>Chiaramonte and Casu, 2013 |
| | **R4** | Equity to debt ratio | Book Value Equity / Book Value of Total Liabilities | Vaziri et al., 2012<br>Othman, 2013<br>Rankov and Kotlica, 2013<br>Pradhan, 2014<br>Hogan, 2014 |
| | **R5** | Debt to equity ratio (financial leverage) | Total Liabilities / Total Equity | Čihák and Schaeck, 2007<br>Afzal et al., 2013<br>Othman, 2013<br>Amel-Zadeh and Meeks, 2013<br>Adeela and Kashif, 2015<br>Miller, Olson and Yeager, 2015 |
| Asset Quality | **R6** | Nonperforming loans to total gross loans ratio | Value of NPLs / Total Value of the Loan Portfolio | Barth et al., 2002<br>Babihuga, 2007<br>Čihák and Schaeck, 2007<br>Ozkan-Gunay and Ozkan, 2007<br>Navajas and Thegeya, 2013<br>Othman, 2013<br>Tuymenbayeva, 2014<br>Adeela and Kashif, 2015 |
| | **R7** | Nonperforming loans net of provisions to capital ratio | (NPLs - the Value of Specific Loan Provisions) / Total Regulatory Capital | Barth et al., 2002<br>Čihák and Schaeck, 2007<br>Navajas and Thegeya, 2013<br>Othman, 2013<br>Tuymenbayeva, 2014<br>Adeela and Kashif, 2015 |

**Source:** Author

Continuation of the table 3.3

| | | | | |
|---|---|---|---|---|
| **Management** | **R8** | Salary to assets ratio | Gross Salary Accrued / Total Assets | Tuymenbayeva, 2014 |
| **Earnings** | **R9** | Return on assets (ROA) | Earnings after Tax / Total Assets | Flannery and Sorescu, 1996<br>Babihuga, 2007<br>Ozkan-Guney and Ozkan, 2007<br>Agarwal and Taffler, 2008<br>Ravi and Pramodh, 2008<br>Chauhan et al., 2009<br><br>Michalak and Uhde, 2012<br>Vaziri et al., 2012<br>Chiaramonte and Casu, 2013<br>Othman, 2013<br>Rankov and Kotlica, 2013<br>Pradhan, 2014<br>Hogan, 2014<br>Diaconu and Oanea, 2014 |
| | **R10** | Return on equity (ROE) | (Gross Income - Gross Expenses) / Average Value of Capital | Babihuga, 2007<br>Čihák and Schaeck, 2007<br>Akhigbe, Madura and Martin, 2007<br>Ozkan-Guney and Ozkan, 2007<br>Agarwal and Taffler, 2008<br>Ravi and Pramodh, 2008<br>Chauhan et al., 2009<br>Chiaramonte and Casu, 2013<br>Navajas and Thegeya, 2013 |
| | **R11** | EBIT to total assets ratio | Earnings Before Interest and Tax / Total Assets | Ravi and Pramodh, 2008<br>Chauhan et al., 2009<br><br>Poghosyan and Čihák, 2011<br>Vaziri et al., 2012<br>Othman, 2013<br>Rankov and Kotlica, 2013<br>Pradhan, 2014<br>Hogan, 2014 |
| | **R12** | Net interest margin | (Interest Income - Interest Expenses) / Earning Assets | Adeela and Kashif, 2015 |
| | **R13** | Interest rate spread | Lending Rate – Deposit Rate | Safdary, Scannell and Ohanian, 2005<br>Adeela and Kashif, 2015 |

**Source:** Author

Continuation of the table 3.3

| | | | | |
|---|---|---|---|---|
| **Liquidity** | **R14** | Working capital to total assets ratio | (Current Assets – Current Liabilities) / Total Assets | Ozkan-Guney and Ozkan, 2007<br>Ravi and Pramodh, 2008<br>Chauhan et al., 2009<br><br>Vaziri et al., 2012<br>Othman 2013<br>Rankov and Kotlica, 2013<br>Pradhan, 2014<br>Hogan, 2014 |
| | **R15** | Current ratio | Average Current Assets / Average Demand Deposit Liabilities | Ozkan-Guney and Ozkan, 2007<br>Chiaramonte and Casu, 2013 |

**Source:** Author

As seen from Table 3.3 these 15 variables are widely used by studies devoted to bank financial soundness, distress, failure and bankruptcy and reflect the nature of the banking sector. Also they are a part of IMF's FSI (R1, R2, R3, R6, R7, R9, R10 and R15) and prudential norms of Kazakhstan banks (R1, R2, R3, R5, R6, R7, R10, R12, R13 and R15).

A set of 15 selected indicators will be used in all empirical chapters to identify the structure of the Kazakhstan banking sector by degree of financial soundness (Appendix 3A). In Chapter 4 indicators R4, R9, R11 and R14 are used to test the ability of Altman's models to predict bank financial unsoundness. Chapter 5 will employ the results of the five principal components calculated from these variables to construct prediction models of bank financial unsoundness by MDA, logit and probit techniques.

### 3.3.2 Descriptive Analysis – Step 2

Descriptive statistics were calculated using annual data for the period from 1st January, 2008 to 1st January 2014 and collected from reports of the National Bank of Kazakhstan and from the annual financial reports of all commercial Kazakhstan banks.

The descriptive analysis contains two parts of ratio analysis and the demarcation of financial soundness limits. Ratio analysis is organized by five areas of capital adequacy, assets quality, management, earnings and liquidity. First of all, for each bank median of ratios were calculated and the results are presented in tables. Second, median values of ratio for each period were computed and presented in graphs. Demarcation of financial soundness limits were derived by quartile intervals.

Demarcation of financial soundness limits is the main result of descriptive statistics. These limits were defined using the quartile intervals. The IMF (2012) in its Global Financial Stability Report (GFSR) analysed eight banking financial stability indicators of banks using a sample of the Euro Area, Europe (noneuro area), Western Hemisphere and Asia countries. All indicators were divided into quartiles[8] and presented in a table. Cells in the table showed values in the worst quartile shaded in red, values in the next-to-worst quartile shaded in yellow and the rest in green.

Following the Global Financial Stability Report (IMF, 2012), quartiles as statistical tools are used to set the limits of financial soundness in banks. Also, as was mentioned in section 3.2.2, the researcher followed Gaganis et al. (2006) and Ioannidis et al. (2010) who classified banks into three groups of the worst quartile for unsound banks, the next-to-worst quartile for risky banks and the remaining two quartiles for sound banks.

The second quartile or median is a “middle” value in a set of data. A median is determined by ranking the data from the largest to smallest and then identifying the middle. The average and median can be the same or nearly the same if the population distribution is bell-shaped and they are different for a heavy-tailed distribution. The selected sample is not normally distributed (Appendix 3B, 3C) and therefore the mean and median are different. For this study the median was chosen because the mean can be too strongly influenced by a small number of outlying values. So, in our case the two quartiles above the median reveal sound banks. Two lower quartiles, respectively, reveal risky and unsound banks.

It is necessary to note that the proposed technique of demarcation of financial soundness limits using financial ratios is of interest for academicians and practitioners. Limits are set for all 15 financial ratios. For some ratios there are tight thresholds defined by national prudential and international legislation. For instance, the IMF Guide (2006) defined applicable level for the R1 capital adequacy ratio (CAR) at 10%. The National Bank (2005b) set a minimum value at 10% and Basel II set 8% for the R2 regulatory capital to risk-weighted assets ratio; the R3 regulatory Tier 1 capital to risk-weighted assets ratio was set at 11% and 6% respectively. The R15 current ratio is limited by prudential normative levels and the minimal value is 0.3. There are no strong ratio requirements for the R4 Equity to debt ratio, the R8 salary to total assets, the R11 earnings before interest

8 A quartile is one of the three points that divide a range of data or population into four equal parts. The first quartile (also called the lower quartile) is the number below which lays 25 percent of the bottom data. The second quartile (the median) divides the range in the middle and has 50 percent of the data below it. The third quartile (also called the upper quartile) has 75 percent of the data below it and the top 25 percent of the data above it.

and taxes (EBIT) to assets and the R14 working capital to total assets.

Commonly, general limits of financial soundness set thresholds by the minimum values of ratios. Some ratios do not have general limits and are assessed only in comparison or in dynamics. The demarcation of financial soundness limits sets the limits to the coefficients for the degree of bank financial soundness by selecting a banking sector at a particular time. Calculated limits do not claim to be the general limits. This technique is a useful tool for the grouping of banks by the degree of financial soundness in countries where not all banks have reliable credit ratings. For example, in Kazakhstan during last fifteen years, just 12 to 26 banks from 38 had ratings established by Standard & Poors, Fitch or Moody's according to the Kazakhstan Stock Exchange (kase.kz).

### 3.3.3 Principal Component Analysis – Step 3

The third step of the cluster based methodology is PCA. PCA was carried out on annual data for the period from 1st January, 2008 to 1st January 2014 for all commercial Kazakhstan with 256 observations in total. The process is divided into four parts by analysis of the correlation of the variables, extraction of the principal components, rotation of the principal components to simplify structure and interpretation of the principal components.

PCA was used to resolve the problem of multicollinearity and to reduce the data dimensionality. PCA divides a set of variables into a small number of groups called principal components. The classification is made according to the criterion of correlation between the variables. One principal component combines a few variables closely correlated with each other and not or weakly correlated with other variables that constitute the other principal component. Thus, by applying PCA to the unsystematized dataset, several macro variables that describe different characteristics of a bank were obtained.

The PCA has advantages of the robustness of the least squares approach to approximating the covariance or correlation matrix and of the relative simplicity of the technique (Jeffers, 1988).

The principal components have made it possible to reduce the dimensionality of the problem and pass to the orthogonal space which is obviously an important step before the implementation of cluster analysis procedures with the Euclidean metric.

PCA was used for data reduction purpose and 3 variables (R8, R10, R14) were excluded from the set of 15 variables. Based on the results of PCA, 12 indicators were isolated.

They explain 5 principle components of capital adequacy, return on assets, profitability, asset quality (NPL), liquidity and leverage.

### 3.3.4 Cluster Analysis – Step 4

Cluster analysis was applied for two points in time on 1st January, 2008 and 1st January, 2014. These dates were chosen with the aim of examining the evolution of clusters over time. Analysis had been performed for all 34 banks of Kazakhstan representing the banking system on 1st January, 2008 and for 37 banks on 1st January, 2014. Zhilstroysberbank was excluded as the state owns 100% of its equity and it specializes in mortgage lending, thus giving abnormal values to its financial ratios. Data are collected from the reports of the National Bank of Kazakhstan and from the annual financial reports of all commercial Kazakhstan banks.

The fourth step of the cluster based methodology is a clustering of the banking sector by the extent of financial soundness. It contains two parts of cluster identification based on the five principle components obtained by PCA and the calculation of the medians of financial ratios for each cluster.

Cluster analysis identifies compact groups of objects remote from each other and searches for "natural" splitting of a set into the areas of object clustering. It is used when source data are presented as the matrices of proximity or the distances between objects or points in a multidimensional space. The most common are the second type of data on which the cluster analysis is focused to identify some geometrically remote groups within which the objects are close. The selection of distance between the objects is the focal point of the research. It largely affects the final partitioning of objects to classes at a given partitioning algorithm. Cluster analysis was performed by the "k-means" method. According to this method, a gap between clusters derived from the increase in the sum of the squared distances of objects to the middle of clusters resulting from their fusion.

In this study a sample of banks was split into three clusters for the two dates of 1st January, 2008 and 1st January, 2014. Banks are clustered according to their common features, which should be identified and interpreted. These can be captured only through selected variables. The next part of the clustering is the calculation of the median values of the financial ratios for each cluster.

### 3.3.5 Interpretation of Clusterization Results – Step 5

The final step of the cluster based methodology is an interpretation of the clusterization results which consists of a final grouping of clusters using limits of financial soundness and an interpretation of the structure of the banking sector by the degree of financial soundness.

The final grouping of clusters was made using the limits of financial soundness in the descriptive analysis. The median values of the financial ratios calculated for each cluster at the previous step correspond with the limits of financial soundness. Interpretation of cluster results is usually carried out using financial ratios even if cluster analysis was performed on the principal components or factors (Dao and Khanh, 2014, Şchiopu, 2010, Satina, 2008). Financial ratios reflect the distinctive features and characteristics of each cluster. They help to give brief summaries of the common characteristics of the obtained clusters. For example, Dao and Khanh (2014) run PCA and cluster analysis to recognize vulnerable banks before they fail and to show warning indicators which they have in common. Interpretation of each cluster considers the values of the financial ratios and not the components to characterize the cluster's peculiarities. The interpretation of groups of banks offers information in a broader perspective, instead of analyzing each bank individually.

Clusters are assigned a red shading to indicate a value in the 1st quartile of "Unsound Banks"; values of the 2nd quartile of "Risky Banks" are shaded in yellow and the rest as "Sound Banks" are shaded in green. The researcher suggests distributing the banks of each cluster into groups according to the degree of financial soundness using the principle of colour predominance. At the same time the special status of the red colour is emphasized, where its presence in each cluster of more than 20% decreases it to one level of financial soundness.

20% is defined as a threshold according the Pareto Principle which is also known as the 80/20 rule. This principle means that roughly 80% of the effects come from 20% of the causes (Newman, 2004). 20% of 12 indicators is 2.4 and thus, if more than 2 indicators are marked red, the financial soundness degree of the group decreases to one level.

The 2 groups of banks obtained on 1st January, 2008 and the 3 groups on 1st January, 2014 according to the degree of financial soundness, are analyzed by the median values of each financial ratio. This analysis helps to detect changes in the structure of the banking sector according to the degree of financial soundness during the study period. These changes are associated with the migration of banks between groups and the emergence of new group of banks.

When analyzing the financial soundness of the country's banking sector as a whole, the researcher assumed that it may contain banks with different degrees of soundness in the sound, risky and unsound classification. Obviously, if financial soundness is considered, the banks of developed countries will have higher indicators than banks in developing countries. For example, the standards of high financial soundness for banks in USA and Europe are completely different from banks in Kazakhstan. Thresholds of financial soundness indicators are specific to each country. The proposed methodology identifies the structure of a banking sector of any country and calculates individual thresholds for the indicators of bank financial soundness for the specific country.

### 3.3.6 Limitations of Study

According to the opinion of Sclove (2001) and Marsh et al. (2003) clustering depends on the specification of the variables, the measure of dissimilarity or similarity, and the clustering procedure. There is no right or wrong cluster analysis solution but only different viewpoints of the same set of data. The subjectivity is implicit in the process of analysis in general.

The quality of the assessment of financial soundness depends on the quality of the source data. In this regard the study had certain limitations. The method of data collection for the quantitative study was limited to secondary sources. The researcher could not control the quality of information from the prudential norm reports of the National Bank and the financial statements of commercial banks. Using ratios calculated from financial statements is a matter of concern. However, they are still helpful in assessing bank financial soundness (Othman, 2013). Despite the subjectivity of the obtained limits of financial soundness, there is a major advantage. The proposed cluster based methodology sets limits for Kazakhstan banks which reflect the real situation in the Kazakhstan banking sector. Moreover, this methodology is suitable and helpful in setting limits for every banking sector of any country.

## 3.4 Descriptive Analysis

This section presents the descriptive statistics of the selected variables for the Kazakhstan banking sector. The results of descriptive analysis provide the limits which divide the Kazakhstan banking sector into sound, risky and unsound banks. It is necessary to note that these limits serve as a flag and not as standards in the process of interpretation relating to judgmental identification of bank clusters.

### 3.4.1 Capital Adequacy

**Capital Adequacy** ensures that a bank maintains a certain level of equity funding, corresponding to the nature and the size of the risks associated with its activity and the management's ability to identify, properly assess, mitigate and control these risks in a timely manner. In assessing capital adequacy, it is necessary to consider the impact of credit, market and other risks on the financial condition of a bank, as the capital should conform to the accepted risks. The type and level of risks inherent in a bank's activities should determine the amount of equity that banks must maintain above the minimum level stipulated by the regulatory bodies to ensure sustainability in stressful situations.

The first selected ratio **R1** is the equity to total assets or **capital adequacy ratio** (CAR). This is an indicator of independence, since it shows the percentage of a bank's assets covered by shareholders' equity. The remainder of the assets is funded by borrowed funds. The higher the ratio, the more likely it is that a bank will be able to pay off debts at the expense of the permanent capital of funds provided by shareholders. Equity capital never has to be repaid and is permanent, secure funding of bank's risk assets.

**R1** (CAR) = Equity / Total Assets (3.1)

*"From a supervisory point of view, large exposures are defined as one or more credit exposures to the same individual or group that exceed a certain percentage of regulatory capital such as 10 percent. It is intended to be applicable at the level of the individual deposit taker"* (IMF, 2006; p. 189).

**R2 regulatory capital to risk-weighted assets** and **R3 regulatory Tier 1 capital to risk-weighted assets** are the second and third indicators and are the calculation of minimum common requirements for capital to credit, market and operational risks. The capital to assets ratio is calculated using the definition of regulatory capital and risk-weighted assets. They can be assigned to the minimum equity of banks requested by the Basel Accords (BCBS, 2010) and the prudential standards of the National Bank of Kazakhstan (National Bank, 2005b).

For **R2** regulatory capital to risk-weighted assets and **R3** regulatory Tier 1 capital to risk-weighted assets calculations the same ratio of equity to assets **R1** is used, with corrections made to equity and assets according to the Basel Accord requirements (BCBS, 2010).

According to the Basel Accord Tier 1 Capital (**R3**) must be at least 6.0% of risk-weighted assets at all times and regulatory capital to risk-weighted assets (**R2**) must be at least 8.0% of risk-weighted assets at all times.

The fourth value **R4** is **the equity to debt ratio** used by Altman in the modified four-factor model. Originally Altman calculated it as the market value of equity to the book value of total liabilities. "*At a later point*", he substituted "*the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z') and for non-manufacturers (Z")*" (Altman, 2000; p.13).

**R4** = Book Value of Equity / Book Value of Total Liabilities (3.2)

Indicator **R5** is the **debt to equity ratio (DER)** or the financial leverage ratio. The higher is the ratio, the greater is a bank's dependence on debt and the lower is the financial soundness of banks. "*Debt to equity or leverage ratios are considered as the cornerstones of capital determinants*" (Adeela and Kashif, 2015; p13).

**R5 (DER)** = Total Liabilities / Total Equity (3.3)

The interpretation of DER should be undertaken in comparison with past periods and competitors. In some cases "*higher DER shows that the company has risky investment because higher debt leads to more interest paid by the company*". On the other hand a high DER could mean that "*banks are growth-oriented and have an easy approach to capital*" (Adeela and Kashif, 2015; p.13). Generally this is a sound measure when earnings are rising but it can be a problem when earnings are under pressure.

The median of selected capital adequacy ratios is presented in Table 3.4

**Table 3.4: Median of Capital Adequacy Ratio, 01.01.2008 – 01.01.2014**

| Banks | Capital adequacy ratio (CAR) | Regulatory capital to risk-weighted assets ratio | Regulatory Tier 1 capital to risk-weighted assets ratio | Equity to debt ratio | Debt to equity ratio (financial leverage) |
|---|---|---|---|---|---|
| | R1 | R2 | R3 | R4 | R5 |
| 1 | 2 | 3 | 4 | 5 | 6 |
| Al Hilal Islamic Bank | 0.894 | 0.878 | 1.259 | 8.801 | 0.120 |
| Alliance Bank | 0.126 | 0.089 | 0.109 | 0.144 | 5.588 |
| AsiaCredit Bank | 0.401 | 0.375 | 0.635 | 0.669 | 1.495 |
| ATF Bank | 0.128 | 0.090 | 0.122 | 0.139 | 7.196 |
| Bank Astana-Finance | 0.222 | 0.218 | 0.253 | 0.296 | 4.011 |

**Source:** Author

Continuation of Table 3.4

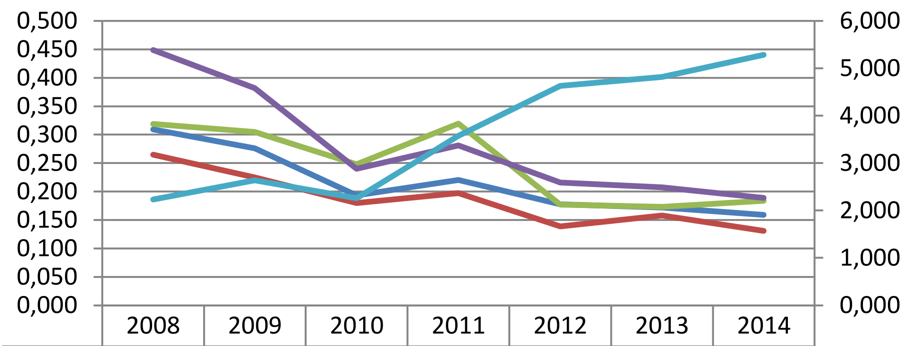
| 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Bank Centercredit | 0.129 | 0.085 | 0.106 | 0.147 | 6.787 |
| Bank Kassa Nova | 0.798 | 0.673 | 0.601 | 3.954 | 0.253 |
| Bank Positive Kazakhstan | 0.415 | 0.350 | 0.640 | 0.638 | 1.567 |
| Bank RBK | 0.644 | 0.589 | 0.689 | 1.813 | 0.552 |
| BTA Bank | 0.174 | 0.138 | 0.138 | 0.192 | 4.732 |
| Citibank of Kazakhstan | 0.125 | 0.089 | 0.214 | 0.143 | 7.015 |
| Delta Bank | 0.234 | 0.218 | 0.203 | 0.302 | 3.310 |
| DO VTB Bank (Kazakhstan) | 0.281 | 0.281 | 0.308 | 0.391 | 2.556 |
| Eurasian Bank | 0.120 | 0.075 | 0.094 | 0.137 | 7.301 |
| Eximbank Kazakhstan | 0.193 | 0.180 | 0.213 | 0.240 | 4.163 |
| ForteBank | 0.297 | 0.218 | 0.363 | 0.423 | 2.363 |
| Halyk Bank of Kazakhstan | 0.128 | 0.092 | 0.120 | 0.143 | 7.017 |
| TPBK | 0.338 | 0.323 | 1.882 | 0.510 | 1.960 |
| Kaspi Bank | 0.143 | 0.085 | 0.094 | 0.161 | 6.222 |
| Kazinvestbank | 0.162 | 0.136 | 0.162 | 0.191 | 5.241 |
| Kazkommertsbank | 0.162 | 0.123 | 0.123 | 0.187 | 5.342 |
| Nurbank | 0.176 | 0.164 | 0.192 | 0.209 | 4.787 |
| Qazaq Banki | 0.474 | 0.478 | 0.575 | 0.900 | 1.111 |
| SB Alpha-Bank | 0.162 | 0.114 | 0.127 | 0.193 | 5.181 |
| SB Bank of China in Kazakhstan | 0.206 | 0.180 | 0.761 | 0.260 | 3.846 |
| SB Home Credit and Finance Bank | 0.314 | 0.214 | 0.216 | 0.459 | 2.180 |
| SB HSBC Bank Kazakhstan | 0.106 | 0.090 | 0.197 | 0.119 | 8.431 |
| SB KZI Bank | 0.556 | 0.520 | 0.826 | 1.256 | 0.796 |
| SB NB of Pakistan in Kazakhstan | 0.803 | 0.775 | 0.841 | 4.071 | 0.246 |
| SB PNB – Kazakhstan | 0.826 | 0.785 | 0.966 | 4.762 | 0.210 |
| SB RBS (Kazakhstan) | 0.151 | 0.148 | 0.443 | 0.177 | 5.672 |
| SB Sberbank | 0.143 | 0.129 | 0.155 | 0.166 | 6.010 |
| SB Taib Kazakh Bank | 0.794 | 0.569 | 0.777 | 1.996 | 0.501 |
| Shinhan Bank of Kazakhstan | 0.791 | 0.782 | 1.195 | 7.837 | 0.307 |
| Temirbank | 0.143 | 0.078 | 0.090 | 0.163 | 6.007 |
| Tsesnabank | 0.116 | 0.092 | 0.094 | 0.129 | 7.749 |
| Zaman-Bank | 0.799 | 0.772 | 0.690 | 3.587 | 0.279 |

*The values of Alliance Bank, BTA Bank and Temirbank are given without data of 2009 and 2010 due to restructuring

**Source:** Author

It can be seen from the Table 3.4, that capital adequacy ratios vary considerably. For example, CAR (R1) has a minimum value at 0.106 and a maximum value at 0.894; regulatory capital to risk-weighted assets ratio (R2) has a minimum value at 0.075 and a maximum value at 0.878; regulatory Tier 1 capital to risk-weighted assets ratio (R3) has minimum value at 0.109 and a maximum value at 1.882 over the study period. Small banks such as SB Taib Kazakh Bank, Shinhan Bank of Kazakhstan, Bank Kassa Nova, Al Hilal Islamic Bank, Zaman-Bank, SB PNB – Kazakhstan, SB NB of Pakistan in Kazakhstan have the highest values for the CAR (R1), regulatory capital to risk-weighted assets ratio (R2), regulatory Tier 1 capital to risk-weighted assets ratio (R3) and equity to debt ratio (R4). These banks constitute less than 10% of the banking sector's assets. The top 5 largest banks such as Kazkommertsbank, Halyk Bank of Kazakhstan, BTA Bank, Bank Centercredit, SB Sberbank have low mean values of capital adequacy ratios; for example CAR (R1) varies from 0.116 to 0.174, regulatory capital to risk-weighted assets ratio (R2) varies from 0.085 to 0.138, regulatory Tier 1 capital to risk-weighted assets ratio (R3) varies from 0.094 to 0.138 and equity to debt ratio (R4) from 0.129 to 0.192. Small banks have low mean values of debt to equity ratio (R5), ranging from 0.120 to 0.501 while in large banks it ranges from 4.732 to 7.749.

**Figure 3.2: Capital Adequacy Ratios 01.01.2008 – 01.01.2014**




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|
| R1 | 0,309 | 0,276 | 0,193 | 0,220 | 0,178 | 0,172 | 0,159 |
| R2 | 0,265 | 0,225 | 0,180 | 0,197 | 0,139 | 0,158 | 0,131 |
| R3 | 0,319 | 0,305 | 0,248 | 0,320 | 0,177 | 0,173 | 0,184 |
| R4 | 0,449 | 0,382 | 0,240 | 0,281 | 0,216 | 0,208 | 0,189 |
| R5 | 2,231 | 2,634 | 2,257 | 3,578 | 4,631 | 4,820 | 5,281 |

2009 and 2010 are shown without the three restructured institutions of the Alliance Bank, the BTA Bank and the Temirbank.

**Source:** Author

It can be seen from Figure 3.2 that the graphs of the first four ratios of CAR (R1), regulatory capital to risk-weighted assets ratio (R2), regulatory Tier 1 capital to risk-weighted assets ratio (R3) and equity to debt ratio (R4) have the same downtrend during the analyzed period. The curve of the debt to equity ratio (R5) clearly characterize the deterioration in the banks' equity. The debt to equity ratio (R5) has steadily increased from 2.231 in 2008 to 5.281 in 2014.

Finally, the limits of the financial soundness in relation to capital adequacy can be established. Hereinafter, the quartiles will be used as a statistical tool to set the limits for the groups of selected indicators of capital adequacy, assets quality, management, earnings and liquidity. The median of every selected capital adequacy ratio from Table 3.4 was used for the quartile interval calculations. These establish the limits of financial soundness for every selected financial ratio.

Table 3.5 shows the limits of financial soundness for selected capital adequacy ratios.

**Table 3.5: Limits of Financial Soundness for Capital Adequacy Ratios, 01.01.2008 – 01.01.2014**

| Quartile intervals | Capital adequacy ratio (CAR) | Regulatory capital to risk-weighted assets ratio | Regulatory Tier 1 capital to risk-weighted assets ratio | Equity to debt ratio* | Debt to equity ratio (financial leverage) |
|---|---|---|---|---|---|
| | R1 | R2 | R3 | R4 | R5 |
| 1 | <0.143 | <0.098 | <0.130 | <0.164 | >5.923 |
| 2 | 0.143–0.214 | 0.098-0.197 | 0.130-0.235 | 0.164-0.278 | 3.929-5.923 |
| 3 | >0.214 | >0.197 | >0.235 | >0. 278 | <3.929 |

**Source:** Author

### 3.4.2 Asset Quality

**Asset Quality** reflects the amount of existing and potential credit default risk inherent in credit loan, investment portfolios, fixed assets, other assets and other off-balance-sheet transactions. This estimate reflects also the ability of management to identify and measure, monitor and control credit risk. The bank shall demonstrate the reliability of the accounting for possible losses on loans and lease receivables and the assessment of the risk of default on contracts with counterparties, issuers or borrowers. Other risks that may affect the market value of the assets are thus considered. The analysis of the loan portfolio, the investment portfolio and other assets is carried out.

The indicator **R6** is **the ratio of nonperforming loans to total gross loans**. It aims to identify problems with the quality of assets in the loan portfolio. It can be interpreted together with the indicator **R7** as **nonperforming loans net of provisions for losses to**

**capital**. An increase of the factor may indicate a deterioration of the loan portfolio quality, although these indicators tend to be retrospective as non-performing loans are only identified when there is a problem with their servicing. For these ratios to be meaningful, it is important to ensure the appropriate reflection of nonperforming loans in the accounting practice.

The indicator **R6** of nonperforming loans to total gross loans ratio **"***is calculated by taking the value of NPLs as the numerator and the total value of the loan portfolio (including NPLs, and before the deduction of specific loan loss provisions) as the denominator*" (IMF, 2006; p.85).

The indicator **R7** of nonperforming loans net of provisions to capital ratio is computed as the value of NPLs less the value of specific loan provisions divided by capital. Capital is measured as capital and reserves, and, for cross-border consolidated data, is also the total regulatory capital (IMF, 2006).

The indicator **R7** is intended to compare the potential impact of non-performing loans net of provisions to capital. This ratio can be an indicator of the ability of a bank's equity to withstand capital losses caused by non-performing loans. In most cases, however, the impact of nonperforming loan losses on the capital is uncertain, as the creditor for various reasons can expect to recover some of the potential losses from non-performing loans.

An increasing ratio of **R6** and **R7** can serve as a signal of deterioration in the quality of the credit portfolio, although this is typically a backward-looking indicator in that NPLs are identified when such as problems emerge. Appropriate recognition of NPLs is essential for this ratio to be meaningful (IMF, 2006).

The National Bank of Kazakhstan in July of 2015 set the limit values for NPL at 15% from January1, 2015 and at 10% from 1$^{st}$ January, 2016 (National Bank, 2015).

**Table 3.6: Median of Selected Assets Quality Ratios, 01.01.2008 – 01.01.2014**

| Banks | Nonperforming loans to total gross loans | Nonperforming loans net of provisions to capital |
|---|---|---|
| | R6 | R7 |
| 1 | 2 | 3 |
| Al Hilal Islamic Bank | 0.000 | 0.000 |
| Alliance Bank | 0.377 | 2.221 |
| AsiaCredit Bank | 0.035 | 0.032 |
| ATF Bank | 0.121 | 0.878 |

**Source:** Author

Continuation of Table 3.6

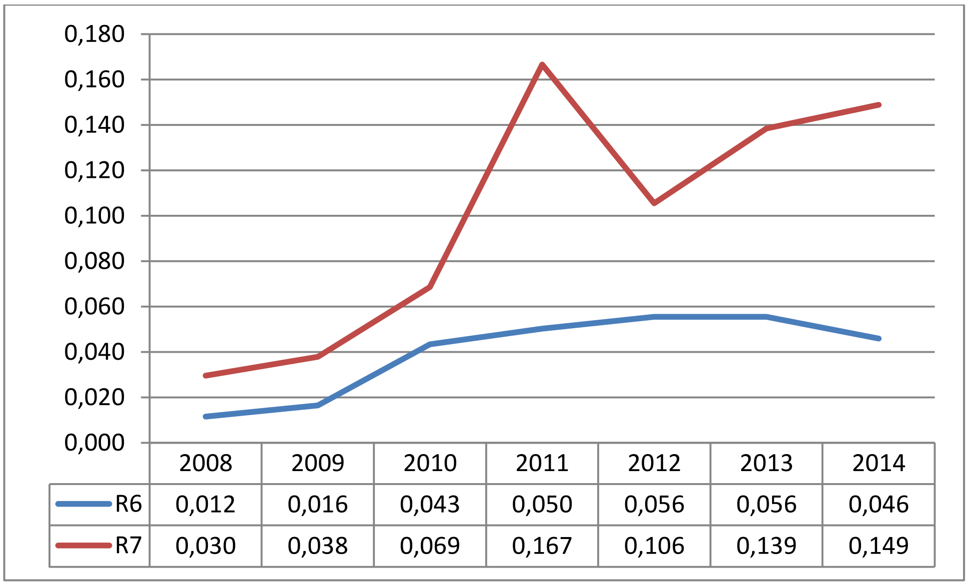
| 1 | 2 | 3 |
|---|---|---|
| Bank Astana-Finance | 0.059 | 0.251 |
| Bank Centercredit | 0.087 | 0.465 |
| Bank Kassa Nova | 0.002 | 0.002 |
| Bank Positive Kazakhstan | 0.111 | 0.125 |
| Bank RBK | 0.002 | 0.002 |
| BTA Bank | 0.484 | 2.001 |
| Citibank of Kazakhstan | 0.019 | 0.056 |
| Delta Bank | 0.006 | 0.029 |
| DO VTB Bank (Kazakhstan) | 0.014 | 0.032 |
| Eurasian Bank | 0.065 | 0.387 |
| Eximbank Kazakhstan | 0.019 | 0.068 |
| ForteBank | 0.059 | 0.152 |
| Halyk Bank of Kazakhstan | 0.149 | 0.633 |
| TPBK | 0.000 | 0.000 |
| Kaspi Bank | 0.065 | 0.363 |
| Kazinvestbank | 0.061 | 0.414 |
| Kazkommertsbank | 0.123 | 0.717 |
| Nurbank | 0.293 | 1.241 |
| Qazaq Banki | 0.009 | 0.012 |
| SB Alpha-Bank | 0.022 | 0.056 |
| SB Bank of China in Kazakhstan | 0.010 | 0.003 |
| SB Home Credit and Finance Bank | 0.021 | 0.080 |
| SB HSBC Bank Kazakhstan | 0.065 | 0.214 |
| SB KZI Bank | 0.037 | 0.055 |
| SB NB of Pakistan in Kazakhstan | 0.015 | 0.009 |
| SB PNB – Kazakhstan | 0.012 | 0.006 |
| SB RBS (Kazakhstan) | 0.036 | 0.078 |
| SB Sberbank | 0.051 | 0.219 |
| SB Taib Kazakh Bank | 0.060 | 0.038 |
| Shinhan Bank of Kazakhstan | 0.000 | 0.000 |
| Temirbank | 0.424 | 2.376 |
| Tsesnabank | 0.033 | 0.148 |
| Zaman-Bank | 0.035 | 0.073 |

*The mean values of Alliance Bank, BTA Bank and Temirbank are given without data of 2009 and 2010 due to restructuring

**Source:** Author

As seen from the Table 3.6, assets quality ratios varies for almost all banks from 0 to 48.4% for nonperforming loans to total gross loans ratio (R6) and from 0 to 238% for nonperforming loans net of provisions to capital ratio (R7). These ratios are significantly high for BTA Bank, ATF Bank, Alliance Bank and Temirbank. Three of these four banks were restructured and partly nationalized temporarily.

**Figure 3.3: Assets Quality Ratios, 01.01.2008 – 01.01.2014**




2009 and 2010 are shown without the restructuring Alliance Bank, BTA Bank and Temirbank

**Source:** Author

The graph of nonperforming loans to total gross loans ratio (R6) nonperforming loans net of provisions to capital ratio (R7) is steadily growing from 2008 to 2014. During this period nonperforming loans to total gross loans ratio (R6) increased by 4 times and nonperforming loans net of provisions to capital ratio (R7) increased by 5 times.

This line chart confirms the deterioration in asset quality of Kazakhstan banks. As mentioned in Section 2.4 the World Bank has ranked Kazakhstan as first in the world for the volume of non-performing credits in the total number of loans granted, having reviewed the year 2012 for most economies in the world (Vorotilov, 2013). A huge value of more than 30% since 2011 made the country the undisputed world "leader" in NPL. IMF (2014) noted the slow progress in resolving NPLs in Kazakhstan. The authorities introduced a special approaches to NPL resolution in 2011 but in 2014 the ratio of non-performing loans had increased to 36% compared to 2.7% in 2007 (Chapter 2).

The median of every selected asset quality ratio from Table 3.6 was used the calculation quartile intervals. These establish the limits of financial soundness for every selected financial ratio. Table 3.7 shows the limits of financial soundness for selected asset quality ratios.

**Table 3.7: Limits of Financial Soundness for Asset Quality Ratios, 01.01.2008 – 01.01.2014**

| Quartile intervals | Nonperforming loans to total gross loans | Nonperforming loans net of provisions to capital |
|---|---|---|
| | R6 | R7 |
| 1 | >0.065 | >0.381 |
| 2 | 0.036-0.065 | 0.076-0.381 |
| 3 | <0.036 | <0.076 |

**Source:** Author

### 3.4.3 Management

**Management** reflects the capability of the board of directors and senior management in their respective roles to identify, measure, monitor and control the risks of bank activities and to ensure that a bank is safe, sound, efficient and in compliance with applicable laws and regulations. "*Sound management practices are demonstrated by active oversight by the board of directors and management; competent personnel; adequate policies, processes, and controls taking into consideration the size and sophistication of the institution; maintenance of an appropriate audit program and internal control environment; and effective risk monitoring and management information systems*" (UFIRS, 1997).

Management in the rating systems is estimated often as the final variable because the quality of a bank's management finds direct expression in the level of liquidity and profitability of a bank, its assets quality and capital adequacy. Therefore, the rating of management corresponds to the average rating of all other components of bank reliability.

Rating systems take account of many factors to derive conclusions about the level of management. Each rating system has scales for the estimation of bank management quality. However, these methods cannot be applied to the estimation of the financial position of a bank at a distance using the information from open sources. It was decided to use **the ratio of gross wages and salaries to assets** as in **R8** for the estimation of management quality following Tuymenbayeva, 2014. It is calculated as the ratio of wages and salaries accrued during the period to average total assets.

**Table 3.8: Medians of Salary to Total Assets Ratio, 01.01.2008 – 01.01.2014**

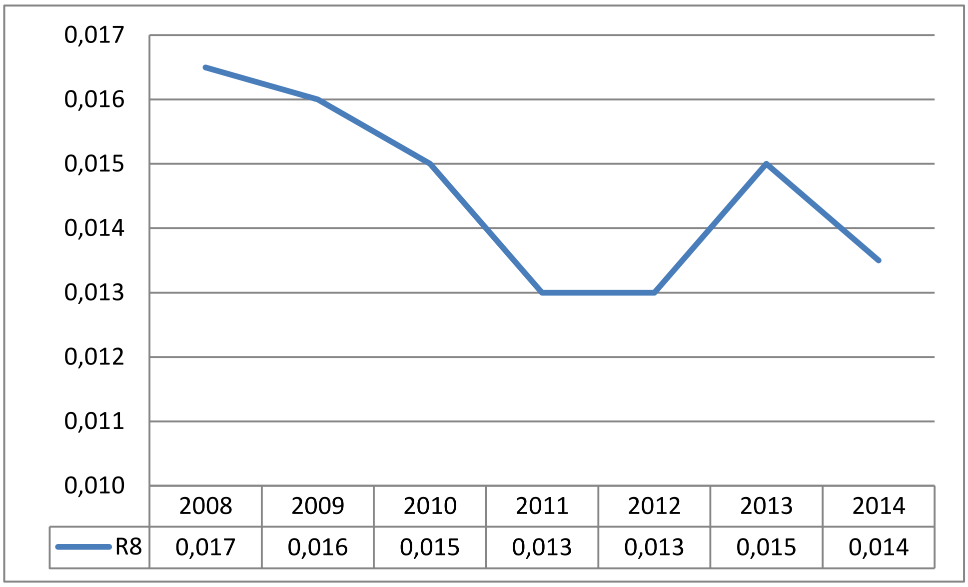
| Banks | Salary to total assets |
|---|---|
| | R8 |
| 1 | 2 |
| Al Hilal Islamic Bank | 0.037 |
| Alliance Bank | 0.014 |
| AsiaCredit Bank | 0.021 |
| ATF Bank | 0.007 |
| Bank Astana-Finance | 0.021 |
| Bank Centercredit | 0.008 |
| Bank Kassa Nova | 0.022 |
| Bank Positive Kazakhstan | 0.033 |
| Bank RBK | 0.015 |
| BTA Bank | 0.007 |
| Citibank of Kazakhstan | 0.003 |
| Delta Bank | 0.007 |
| DO VTB Bank (Kazakhstan) | 0.031 |
| Eurasian Bank | 0.024 |
| Eximbank Kazakhstan | 0.011 |
| ForteBank | 0.011 |
| Halyk Bank of Kazakhstan | 0.008 |
| TPBK | 0.005 |
| Kaspi Bank | 0.018 |
| Kazinvestbank | 0.013 |
| Kazkommertsbank | 0.005 |
| Nurbank | 0.011 |
| Qazaq Banki | 0.020 |
| SB Alpha-Bank | 0.016 |
| SB Bank of China in Kazakhstan | 0.004 |
| SB Home Credit and Finance Bank | 0.029 |
| SB KZI Bank | 0.018 |
| SB NB of Pakistan in Kazakhstan | 0.031 |
| SB PNB – Kazakhstan | 0.018 |
| SB RBS (Kazakhstan) | 0.012 |
| SB Sberbank | 0.013 |
| Shinhan Bank of Kazakhstan | 0.018 |
| Temirbank | 0.015 |
| Tsesnabank | 0.012 |
| Zaman-Bank | 0.017 |

*The values of Alliance Bank, BTA Bank and Temirbank are given without data of 2009 and 2010 due to restructuring

**Source:** Author

As seen from Table 3.8, the medians of salary to total assets ratio (R8) varies from 0.003 to 0.037 for the analyzed banks. The salary to total assets ratio (R8) of the 5 top banks, Kazkommertsbank, Halyk Bank of Kazakhstan, BTA Bank, Bank Centercredit, SB Sberbank has the lowest values from 0.005 to 0.013 and the highest value from 0.017 to 0.037 for the five smallest Shinhan Bank of Kazakhstan, Al Hilal Islamic Bank, Zaman-Bank, SB PNB – Kazakhstan, SB NB of Pakistan in Kazakhstan.

**Figure 3.4: Salary to Total Assets Ratio, 01.01.2008 – 01.01.2014**




2009 and 2010 are shown without the three restructuring Alliance Bank, BTA Bank and Temirbank

**Source:** Author

According to Figure 3.4 the ratio of salary to Total Assets Ratio (R8) is gradually reduced from 0.017 in 2008 to 0.013 in 2011. In 2013 it increased to 0.015 and in 2014 was 0.14.

Selecting this ratio as an indicator, the researcher was guided by the opinion of Tuymenbayeva (2014) that the larger is a bank's staff and the higher are the salaries, the more the bank is focused on risk management and early warning systems, performing additional tests on the bank's health. However, the analysis shows that the large banks have lower value of this ratio than the smaller institutions.

The median of selected salary to total assets ratio (Table 3.8) was used for the calculation of quartile intervals (Table 3.9).

**Table 3.9: Limits of Financial Soundness for Salary to Total Assets Ratio, 01.01.2008 – 01.01.2014**

| Quartile intervals | Salary to total assets |
|---|---|
| | R8 |
| 1 | <0.010 |
| 2 | 0.010-0.015 |
| 3 | >0.015 |

**Source:** Author

### 3.4.4 Earnings

**Earnings** reflect the quality of the management of credit risk resulting in possible losses on loans and additional expenses for the creation of loss provisions and legal costs. The result of a low level of market risk management can be losses from a change in interest rates. Non-routine expenses and uncertain circumstances may influence the level of profitability and future profitability may be decreased by an inability to predict or control the movement of resources and operational costs by a faulty business strategy and by weak or a lack of control of other risks (UFIRS, 1997).

Three profitability indicators are selected. **R9** is **the return on assets** (ROA) calculated as the ratio of earnings after tax to average total assets. It is one of the common operating ratios used to assess bank profitability in addition to indicators such as **R10** of **the net income to average equity** (also known as return on equity or ROE) and **R11** of **the earnings before interest and taxes** (EBIT) to total assets.

**R9** = Earnings after Tax / Total Assets (3.4)

The denominator can be computed at least as the average of the values at the beginning and end of the responding period. However, to calculate the average value it is recommended by IMF (2006) that the most frequent available observation is used.

The ROA figure gives investors the indication of effectiveness of a bank's performance. A higher ROA is preferred because the bank is earning more income.

**R10** is the ratio of the return on equity (ROE) intended to assess the efficiency of banks in using their equity. When considering the dynamics it can also provide information on the long-term sustainability of a bank's capital position.

**R10** = (Gross Income - Gross Expenses) / Average Value of Capital (3.5)

The appropriate rate of ROE could vary. "A rather risk-averse bank might decide that a return on equity of 11 % is sufficient. There is lower volatility then, so the returns tend to be pretty stable. One can expect that the 11 % can be achieved in most years. A risk taking bank possibly axpects a return on equity of 20 %. The increased risk appetite and thus the higher return are associated with higher volatility. It may be that in one year the 20 % can be achieved, while the return in the next year goes down or even is negative" (Wernz, 2014).

**R11** = Earnings before Interest and Tax / Total Assets (3.6)

**R11** is the ratio of earnings before interest and taxes (EBIT) to total assets. It is another version of the return on assets ratio using in the numerator earnings before interest and tax.

Indicators of the efficiency of income and expenses are given by **R12** as **the interest margin or net interest margin** and by **R13** as **the interest rate spread**.

**R12** as the interest margin is the ratio of the difference between the interest income and interest expense to total assets and shows the value of net income interest to interest cost to assets.

**R12** = (Interest Income - Interest Expenses) / Total assets (3.7)

A positive value for this measure shows the effectiveness of bank management decisions. However, non-income generating assets and non-interest paying liabilities have a significant impact on the net interest margin. Non income generating assets limit the possibility for its increase, if the liabilities on which the interest is paid are used to fund the assets. At the same time, non-interest liabilities contribute to the growth of income if they are used to finance assets on which the bank earns high interest.

**R13** as the interest rate spread is calculated as the difference between the average interest rate paid to depositors and the average interest rate earned from borrowers. "*The Guide recommends at a minimum the calculation of the weighted average of all lending and deposit interest rates on loans and deposits (excluding loans and deposits among deposit takers) during a reference period in the portfolio of resident deposit takers. The interest rate spread could also be calculated on a domestically controlled, cross-border consolidated basis, thus providing an indication of profitability, but it would be reflecting activity in different markets*" (IMF, 2006; p.91).

This indicator reveals the impact of interest rates on profit and thus allows superior understanding of the sources of bank profitability and hence the degree of vulnerability of profitable sources. A negative or very low value indicates an ineffective interest rate policy or a loss but a high value also could be a negative sign because high rates are often earned on assets that are excessively risky.

**Table 3.10: Median of Earnings Ratios, 01.01.2008 – 01.01.2014**

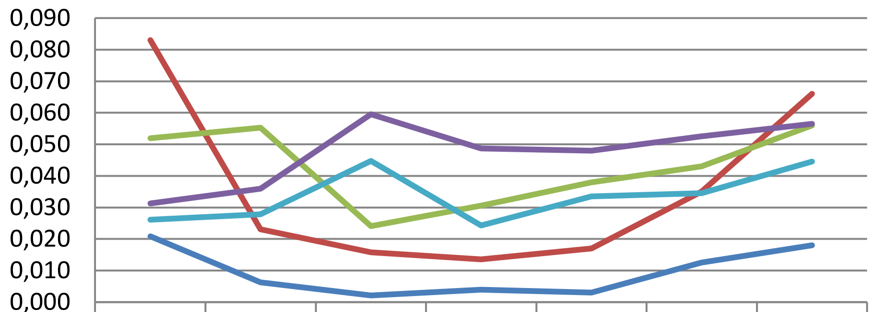
| Banks | Return on assets | Return on equity | Earnings before interest and taxes (EBIT) to assets | Net interest rate margin | Interest rate spread |
|---|---|---|---|---|---|
| | R9 | R10 | R11 | R12 | R13 |
| 1 | 2 | 3 | 4 | 5 | 6 |
| Al Hilal Islamic Bank | 0.006 | 0.009 | 0.003 | 0.035 | 0.036 |
| Alliance Bank | 0.013 | 0.210 | 0.090 | 0.030 | 0.002 |
| AsiaCredit Bank | 0.020 | 0.043 | 0.051 | 0.069 | 0.057 |
| ATF Bank | -0.013 | -0.154 | 0.041 | 0.026 | 0.022 |
| Bank Astana-Finance | -0.005 | -0.011 | 0.031 | 0.066 | 0.052 |
| Bank Centercredit | 0.002 | 0.017 | 0.053 | 0.026 | 0.024 |
| Bank Kassa Nova | -0.001 | -0.003 | 0.073 | 0.098 | 0.087 |
| Bank Positive Kazakhstan | 0.002 | 0.007 | 0.001 | 0.049 | 0.047 |
| Bank RBK | 0.009 | 0.013 | 0.014 | 0.088 | 0.061 |
| BTA Bank | 0.004 | 0.103 | 0.054 | -0.010 | -0.020 |
| Citibank of Kazakhstan | 0.026 | 0.167 | 0.040 | 0.017 | 0.016 |
| Delta Bank | 0.008 | 0.058 | 0.076 | 0.088 | 0.064 |
| DO VTB Bank (Kazakhstan) | 0.002 | 0.009 | 0.052 | 0.057 | 0.048 |
| Eurasian Bank | 0.018 | 0.162 | 0.089 | 0.060 | 0.052 |
| Eximbank Kazakhstan | 0.004 | 0.023 | 0.050 | 0.060 | 0.042 |
| ForteBank | 0.007 | 0.030 | 0.044 | 0.042 | 0.034 |
| Halyk Bank of Kazakhstan | 0.016 | 0.092 | 0.055 | 0.058 | 0.039 |
| TPBK | 0.012 | 0.043 | 0.031 | 0.020 | 0.018 |
| Kaspi Bank | 0.023 | 0.159 | 0.098 | 0.082 | 0.063 |
| Kazinvestbank | 0.001 | 0.011 | 0.053 | 0.036 | 0.024 |
| Kazkommertsbank | 0.002 | 0.013 | 0.059 | 0.057 | 0.032 |
| Nurbank | -0.004 | -0.016 | 0.040 | 0.033 | 0.009 |
| Qazaq Banki | 0.004 | 0.017 | 0.050 | 0.048 | 0.031 |
| SB Alpha-Bank | 0.018 | 0.084 | 0.059 | 0.056 | 0.044 |
| SB Bank of China in Kazakhstan | 0.026 | 0.117 | 0.033 | 0.015 | 0.015 |
| SB Home Credit and Finance Bank | 0.105 | 0.299 | 0.093 | 0.262 | 0.214 |
| SB HSBC Bank Kazakhstan | 0.022 | 0.138 | 0.047 | 0.044 | 0.039 |
| SB KZI Bank | 0.018 | 0.038 | 0.040 | 0.052 | 0.027 |
| SB NB of Pakistan in Kazakhstan | 0.018 | 0.022 | 0.031 | 0.092 | 0.055 |
| SB PNB – Kazakhstan | 0.005 | 0.006 | 0.003 | 0.041 | 0.018 |
| SB RBS (Kazakhstan) | 0.016 | 0.032 | 0.022 | 0.018 | 0.017 |
| SB Sberbank | 0.013 | 0.106 | 0.061 | 0.053 | 0.048 |
| SB Taib Kazakh Bank | 0.010 | 0.028 | 0.019 | 0.046 | 0.038 |
| Shinhan Bank of Kazakhstan | 0.020 | 0.026 | 0.026 | 0.052 | 0.040 |
| Temirbank | 0.006 | 0.009 | 0.064 | 0.047 | 0.018 |
| Tsesnabank | 0.009 | 0.149 | 0.082 | 0.042 | 0.045 |
| Zaman-Bank | 0.010 | 0.017 | 0.042 | 0.062 | 0.024 |

*The average values of Alliance Bank, BTA Bank and Temirbank are given without data of 2009 and 2010 due to restructuring

**Source:** Author

It can be seen from Table 3.10 that earnings ratios vary considerably. For example, the first profitability indicator of return on assets (R9) has a minimum value at -0.013 and a maximum value at 0.105, the return on equity (R10) has a minimum value at -0.154 and a maximum value at 0.299, earnings before interest and taxes (EBIT) to assets (R11) has a minimum value at 0.001 and a maximum value at 0.098 over the study period. Four banks have negative values of return on assets and return on equity.They include ATF Bank, Bank Astana-Finance, Bank Kassa Nova and Nurbank. Net interest rate margin (R12) and Interest rate spread (R13) have minimum values at -0.010 and -0.020 and maximum value at 0.262 and 0.214 respectively. BTA Bank has negative value of net interest rate margin and interest rate spread.

**Figure 3.5: Effectiveness Ratios Dynamics, 01.01.2008 – 01.01.2014**




| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|
| R9 | 0,021 | 0,006 | 0,002 | 0,004 | 0,003 | 0,013 | 0,018 |
| R10 | 0,083 | 0,023 | 0,016 | 0,014 | 0,017 | 0,035 | 0,066 |
| R11 | 0,052 | 0,055 | 0,024 | 0,031 | 0,038 | 0,043 | 0,056 |
| R12 | 0,031 | 0,036 | 0,060 | 0,049 | 0,048 | 0,053 | 0,057 |
| R13 | 0,026 | 0,028 | 0,045 | 0,024 | 0,034 | 0,035 | 0,045 |

2009 and 2010 are shown without the three restructuring banks of Alliance Bank, BTA Bank and Temirbank

**Source:** Author

It can be seen from Figure 3.5 that, during the sample period, return on assets (R9) and return on equity (R10) had the highest value in 2008. They decreased sharply in 2010 and 2011, and returned close to the pre-crisis levels in 2014. The deterioration of earnings before interest and taxes (EBIT) to assets (R11) started from 2009 and in 2014 the indicator reached pre-crisis level.

The lowest values of the net interest rate margin (R12) at 0.031 is observed in 2008 and interest rate spread (R13) at 0.024 in 2011. The peak values for these two indicators are in 2010 at 0.060 and 0.045 respectively. The values of these indicators in 2011 roughly correspond to 2008 and since 2011 they have gradually increased, reaching 0.057 and

0.045 in 2014 respectively.

The median of the earnings ratios from Table 3.10 were used for the calculation of the quartile intervals. This quartile establishes the limits of financial soundness for every selected financial ratio as indicated in the Table 3.11.

**Table 3.11: Limits of Financial Soundness for Earnings Ratios, 01.01.2008 – 01.01.2014**

| Quartile intervals | Return on assets | Return on equity | Earnings before interest and taxes (EBIT) to assets | Net interest rate margin | Interest rate spread |
|---|---|---|---|---|---|
| | R9 | R10 | R11 | R12 | R13 |
| 1 | <0.004 | <0.011 | <0.032 | <0.035 | <0.022 |
| 2 | 0.004-0.009 | 0.011-0.027 | 0.032-0.049 | 0.035-0.050 | 0.022-0.038 |
| 3 | >0.009 | >0.027 | >0.049 | >0.050 | >0.038 |

**Source:** Author

### 3.4.5 Liquidity

**Liquidity** includes the current and expected liquidity position, depending on the forthcoming cash receipts of maturing liquid assets compared with the cash requirements and the quality of management of resources relative to the size, complexity and nature of the risk of a bank.  A bank is required to maintain sufficient liquidity to meet its cash obligations and the needs of clients.

Many indicators can reflect bank liquidity. In fact, the liquidity of banks is their ability to ensure a timely repayment of deposit obligations to customers through their available cash by selling assets or by attracting additional deposits from external sources at a reasonable price. Liquidity is determined by the degree of matching arrangement between assets and liabilities in terms of their value and maturity. In this study **the R14 Working capital to total assets** and **current liquidity ratio** or **current ratio** of **R15** are selected as indicators of liquidity following studies by Ozkan-Guney and Ozkan (2007), Vaziri et al. (2012), Rankov and Kotlica (2013), Chiaramonte and Casu (2013) and Hogan (2014). The **R14** ratio of **Working capital to total assets** is used to measure liquidity. It is an indicator taken from the modified Altman four-factor model for non-manufacturing companies. It is calculated as the ratio of working capital to total assets. Working capital is the difference between current assets and current liabilities. Current assets consist of cash, cash equivalents, marketable securities, short-term accounts receivable and the working capital to total assets ratio shows the bank’s ability to cover its current liabilities.

**R14** = (Current Assets – Current Liabilities) / Total Assets (3.8)

The current liquidity ratio of banks is calculated as the ratio of the average monthly current assets of banks to the average size of demand deposit liabilities including the accrued interest. According to Kazakhstan's prudential standards current assets consist of cash, precious metals, government securities and call deposits that meet certain requirements and loans "overnight" (National Bank, 2005b).

**R15** = Average Current Assets / Average Demand Deposit Liabilities (3.9)

**Table 3.12: Median of Liquidity Ratios, 01.01.2008 – 01.01.2014**

| Banks | Working capital to total assets | Current ratio |
|---|---|---|
| | R14 | R15 |
| 1 | 2 | 3 |
| Al Hilal Islamic Bank | 0.140 | 8.403 |
| Alliance Bank | 0.098 | 1.577 |
| AsiaCredit Bank | -0.808 | 1.124 |
| ATF Bank | -0.405 | 1.103 |
| Bank Astana-Finance | -0.630 | 0.747 |
| Bank Centercredit | -0.644 | 0.796 |
| Bank Kassa Nova | 0.142 | 0.758 |
| Bank Positive Kazakhstan | 0.031 | 1.068 |
| Bank RBK | 0.265 | 1.358 |
| BTA Bank | -0.572 | 1.437 |
| Citibank of Kazakhstan | -0.106 | 0.879 |
| Delta Bank | 0.076 | 1.396 |
| DO VTB Bank (Kazakhstan) | 0.320 | 0.948 |
| Eurasian Bank | -0.023 | 1.154 |
| Eximbank Kazakhstan | -0.165 | 0.556 |
| ForteBank | 0.281 | 0.978 |
| Halyk Bank of Kazakhstan | -0.041 | 1.101 |
| TPBK | 0.068 | 1.274 |
| Kaspi Bank | -0.800 | 1.513 |
| Kazinvestbank | 0.167 | 0.726 |
| Kazkommertsbank | 0.180 | 0.636 |
| Nurbank | -0.077 | 0.835 |
| Qazaq Banki | -0.173 | 1.610 |
| SB Alpha-Bank | -0.068 | 0.898 |
| SB Bank of China in Kazakhstan | 0.112 | 1.051 |
| SB Home Credit and Finance Bank | 0.029 | 1.494 |
| SB HSBC Bank Kazakhstan | 0.066 | 0.997 |
| SB KZI Bank | 0.075 | 1.451 |
| SB NB of Pakistan in Kazakhstan | 0.014 | 2.167 |
| SB PNB – Kazakhstan | 0.493 | 4.198 |
| SB RBS (Kazakhstan) | -0.022 | 0.934 |
| SB Sberbank | -0.125 | 0.864 |
| SB Taib Kazakh Bank | 0.073 | 1.736 |

**Source:** Author

Continuation of Table 3.12

| 1 | 2 | 3 |
|---|---|---|
| Shinhan Bank of Kazakhstan | -0.041 | 1.509 |
| Temirbank | 0.365 | 3.086 |
| Tsesnabank | 0.075 | 0.731 |
| Zaman-Bank | 0.049 | 1.410 |

*The average values of Alliance Bank, BTA Bank and Temirbank are given without data of 2009 and 2010 due to restructuring

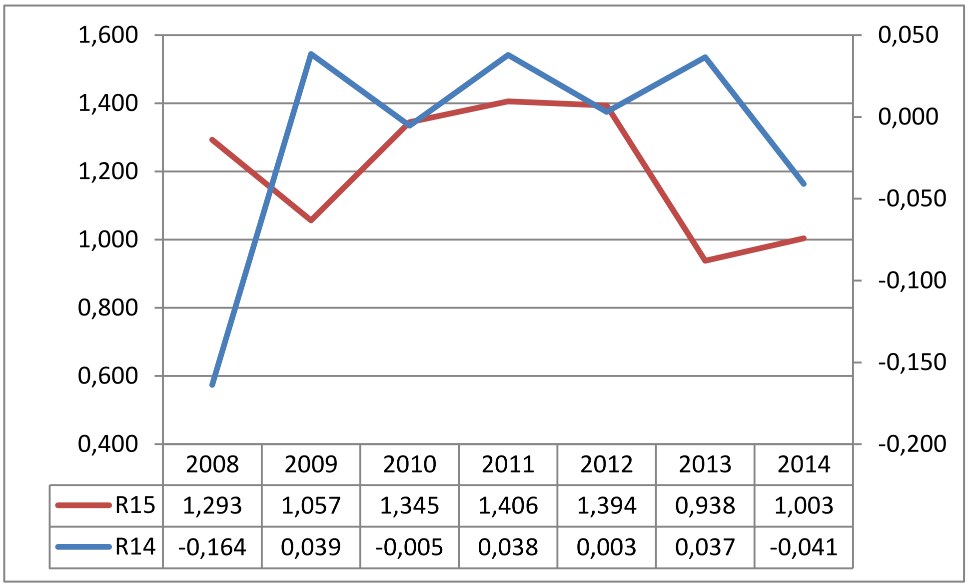
**Source:** Author

16 banks have negative medians of working capital to total assets (R14). The smallest banks mostly have positive values of this ratio, such the Al Hilal Islamic Bank at 0.140, the Zaman-Bank at 0.049, the SB PNB – Kazakhstan at 0.493 and the SB NB of Pakistan in Kazakhstan at 0.014. Only the Shinhan Bank of Kazakhstan has negative value at -0.041, Four of the top 5 largest banks have negative values of working capital to total assets ratios (R14) such as the Halyk Bank of Kazakhstan at -0.041, the BTA Bank at -0.572, the SB Sberbank at-0.125 and the Bank Centercredit at -0.644. Only Kazkommertsbank had a positive value at 0.180.

Altman (1993) included this ratio (R14) of working capital to total assets in the Z" model for non-manufacturing companies (1993) as significant. Also, Othman (2013), Chieng (2013), Rankov and Kotlica (2013) and Pradhan (2014) followed Altman and supported the ability of the indicator to distinguish problem/non-problem banks.

As can be seen from Table 3.12, 22 banks have a current ratio (R15) of above 1. The top 5 largest banks have low level of current ratio (R15) such as the Kazkommertsbank at 0.636, the Halyk Bank of Kazakhstan at 1.101, the BTA Bank at 1.437, the Bank Centercredit at 0.796 and the SB Sberbank at 0.864. The current ratio (R15) of the five smallest banks varies significantly from 1.410 to 8.403.

**Figure 3.6: Liquidity Ratios, 01.01.2008 – 01.01.2014**




2008 is shown without TPBK bank because of its abnormal value

2009 and 2010 are shown without three restructuring banks Alliance Bank, BTA Bank and Temirbank

**Source:** Author

At first glance the graphs which characterize current liquidity looks positive. The value of the current liquidity ratio (R15) was 1.293 in 2008 and then it reached a peak at 1.394 in 2012 and declined to 1.004 in 2014. The working capital to total assets (R14) was negative for three years during the period from 2008 to 2014, in 2008, 2010 and 2014.

The mean values of liquidity ratios (Table 3.12) were used for the calculation of the quartile intervals (Table 3.13):

**Table 3.13: Limits of Financial Soundness for Liquidity Ratios, 01.01.2008 – 01.01.2014**

| Quartile intervals | Working capital to total assets | Current ratio* |
|---|---|---|
| | R14 | R15 |
| 1 | <-0.099 | <0.884 |
| 2 | -0.099-0.040 | 0.884-1.114 |
| 3 | >0.040 | >1.114 |

**Source:** Author

### 3.4.6 Demarcation of Financial Soundness Limits

The main results of the descriptive analysis are derived from the quartile intervals for all five groups of financial indicators of capital adequacy, assets quality, management, earnings and liquidity. These quartile intervals are the limits of the financial soundness that allowed the researcher to divide the banking sector into three groups as was described at the beginning of this section as follows:

1st Limit “Unsound Banks”,
2nd Limit “Risky Banks”,
3rd Limit “Sound Banks”

These limits will be used for Step 5 of the cluster based methodology of the assessment of financial soundness to determine the structure of the banking sector:

**Table 3.14: Limits of Financial Soundness, 01.01.2008 – 01.01.2014**

| Selected Variables | | **1st Limit “Unsound Banks** | **2nd Limit “Risky Banks”** | **3rd Limit “Sound Banks”** |
|---|---|---|---|---|
| Capital adequacy ratio (CAR) | R1 | <0.143 | 0.143–0.214 | >0.214 |
| Regulatory capital to risk-weighted assets ratio | R2 | <0.098 | 0.098-0.197 | >0.197 |
| Regulatory Tier 1 capital to risk-weighted assets ratio | R3 | <0.130 | 0.130-0.235 | >0.235 |
| Equity to debt ratio | R4 | <0.164 | 0.164-0.278 | >0. 278 |
| Debt to equity ratio (financial leverage) | R5 | >5.923 | 3.929-5.923 | <3.929 |
| Nonperforming loans to total gross loans | R6 | >0.065 | 0.036-0.065 | <0.036 |
| Nonperforming loans net of provisions to capital | R7 | >0.381 | 0.076-0.381 | <0.076 |
| Salary to total assets | R8 | <0.010 | 0.010-0.015 | >0.015 |
| Return on assets | R9 | <0.004 | 0.004-0.009 | >0.009 |
| Return on equity | R10 | <0.011 | 0.011-0.027 | >0.027 |
| Earnings before interest and taxes (EBIT) to assets | R11 | <0.032 | 0.032-0.049 | >0.049 |
| Net interest rate margin | R12 | <0.035 | 0.035-0.050 | >0.050 |
| Interest rate spread | R13 | <0.022 | 0.022-0.038 | >0.038 |
| Working capital to total assets | R14 | <-0.099 | -0.099-0.040 | >0.040 |
| Current ratio | R15 | <0.884 | 0.884-1.114 | >1.114 |

*The average values of Alliance Bank, BTA Bank and Temirbank are given without data of 2010 and 2011 due to restructuring

**Source:** Author

### 3.5 Results: Principal Component Analysis

The next important step of the cluster based methodology of assessment of the banking sector’s financial soundness is data reduction using PCA. PCA includes analysis of the correlation of variables, extraction, rotation and interpretation of factors. PCA was carried out on annual data for the period from 1st January, 2008 to 1st January 2014 for all commercial Kazakhstan with 256 observations in total.

### 3.5.1 Analysis of Correlation of Variables

A summary of the selected set of financial indicators that have been analysed in the previous section is shown in Table 3.15.

**Table 3.15: The Financial Indicators**

| Financial Ratios | Variables for statistical analysis |
|---|---|
| Capital adequacy ratio (CAR) | R1 |
| Regulatory capital to risk-weighted assets ratio | R2 |
| Regulatory Tier 1 capital to risk-weighted assets ratio | R3 |
| Equity to debt ratio | R4 |
| Debt to equity ratio (financial leverage) | R5 |
| Nonperforming loans to total gross loans ratio | R6 |
| Nonperforming loans net of provisions to capital ratio | R7 |
| Salary to assets ratio | R8 |
| Retained earnings to total assets ratio | R9 |
| Return on equity ratio | R10 |
| EBIT to total assets ratio | R11 |
| Net interest margin | R12 |
| Interest rate spread | R13 |
| Working capital to total assets ratio | R14 |
| Current ratio | R15 |

**Source:** Author

As was noted in section 3.3.2 the selected sample is not normaly distributed (Appendixces 3B, 3C). This set of indicators gives a table of paired correlation coefficients calculated by Spearman. Spearman's correlation matrix is used because it does not make any assumptions about the distribution of the data. It does not require a normal distribution (Zimmerman and Zumbo, 1993) (Table 3.16)

The correlation matrix is the table that shows all pairs of correlation coefficients for a set of indicators. It shows the correlation coefficients between each pair, for 15 variables, arranged so that each variable is identified on each row and on each column, with the coefficient listed in the cells and defined by the rows and columns. In SPSS, before finding a solution to a set of variables to make it more sensible, PCA is conducted in order to look at the intercorrelation between variables.

**Table 3.16: Paired Correlation Coefficients of Selected Indicators (Spearman's rho)**

| | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| R1 | 1.000 | 0.882** | 0.760** | 0.994** | -0.787** | -0.247* | -0.165 | -0.044 | 0.070 | -0.268* | -0.113 | 0.217* | 0.076 | 0.139 | 0.123 |
| R2 | 0.882** | 1.000 | 0.889** | 0.882** | -0.675** | -0.256* | -0.167 | -0.094 | -0.088 | -0.446** | -0.205 | 0.145 | 0.053 | 0.164 | 0.033 |
| R3 | 0.760** | 0.889** | 1.000 | 0.745** | -0.537** | -0.343** | -0.253* | -0.020 | -0.052 | -0.407** | -0.254* | 0.023 | -0.024 | 0.137 | 0.157 |
| R4 | 0.994** | 0.882** | 0.745** | 1.000 | -0.793** | -0.227* | -0.147 | -0.027 | 0.077 | -0.263* | -0.110 | 0.243* | 0.085 | 0.149 | 0.108 |
| R5 | -0.787** | -0.675** | -0.537** | -0.793** | 1.000 | 0.035 | 0.353** | -0.095 | 0.131 | 0.072 | 0.315** | -0.048 | 0.095 | -0.217* | -0.075 |
| R6 | -0.247* | -0.256* | -0.343** | -0.227* | 0.035 | 1.000 | 0.784** | -0.043 | -0.240* | 0.036 | -0.043 | -0.307** | -0.576** | 0.079 | -0.028 |
| R7 | -0.165 | -0.167 | -0.253* | -0.147 | 0.353** | 0.784** | 1.000 | -0.192 | -0.061 | -0.135 | 0.183 | -0.111 | -0.378** | -0.016 | -0.043 |
| R8 | -0.044 | -0.094 | -0.020 | -0.027 | -0.095 | -0.043 | -0.192 | 1.000 | 0.169 | 0.231* | 0.186 | 0.152 | 0.124 | 0.042 | 0.263* |
| R9 | 0.070 | -0.088 | -0.052 | 0.077 | 0.131 | -0.240* | -0.061 | 0.169 | 1.000 | 0.739** | 0.583** | 0.326** | 0.317** | 0.081 | 0.283** |
| R10 | -0.268* | -0.446** | -0.407** | -0.263* | 0.072 | 0.036 | -0.135 | 0.231* | 0.739** | 1.000 | 0.502** | 0.023 | 0.056 | 0.012 | 0.179 |
| R11 | -0.113 | -0.205 | -0.254* | -0.110 | 0.315** | -0.043 | 0.183 | 0.186 | 0.583** | 0.502** | 1.000 | 0.226* | 0.244* | -0.060 | 0.160 |
| R12 | 0.217* | 0.145 | 0.023 | 0.243* | -0.048 | -0.307** | -0.111 | 0.152 | 0.326** | 0.023 | 0.226* | 1.000 | 0.806** | 0.058 | 0.006 |
| R13 | 0.076 | 0.053 | -0.024 | 0.085 | 0.095 | -0.576** | -0.378** | 0.124 | 0.317** | 0.056 | 0.244* | 0.806** | 1.000 | -0.008 | -0.095 |
| R14 | 0.139 | 0.164 | 0.137 | 0.149 | -0.217* | 0.079 | -0.016 | 0.042 | 0.081 | 0.012 | -0.060 | 0.058 | -0.008 | 1.000 | 0.237* |
| R15 | 0.123 | 0.033 | 0.157 | 0.108 | -0.075 | -0.028 | -0.043 | 0.263* | 0.283** | 0.179 | 0.160 | 0.006 | -0.095 | 0.237* | 1.000 |

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

**Source:** Author

In order to do PCA, all selected variables should be correlated fairly well, but not perfectly correlated. Thus, a correlation matrix table can be used to check the pattern of relationships among the variables.

Table 3.16 shows mediocre correlation between most of the variables and significant relationships exist between some ratios. For example, the capital adequacy ratio (R1), regulatory capital to risk-weighted assets ratio (R2), regulatory Tier 1 capital to risk-weighted assets ratio (R3), equity to debt ratio (R4) and equity to debt ratio (R5) variables are highly correlated. From the economic point of view, it is understandable because these four indicators characterize capital adequacy.

Table 3.17 lists of the variables and their communality.

**Table 3.17: Communality Coefficients**

| | | Initial | Extraction |
|---|---|---|---|
| R1 | Capital adequacy ratio (CAR) | 1.000 | 0.902 |
| R2 | Regulatory capital to risk-weighted assets ratio | 1.000 | 0.900 |
| R3 | Regulatory Tier 1 capital to risk-weighted assets ratio | 1.000 | 0.648 |
| R4 | Equity to debt ratio | 1.000 | 0.587 |
| R5 | Debt to equity ratio (financial leverage) | 1.000 | 0.727 |
| R6 | Nonperforming loans to total gross loans ratio | 1.000 | 0.818 |
| R7 | Nonperforming loans net of provisions to capital ratio | 1.000 | 0.590 |
| R8 | Salary to assets ratio | 1.000 | 0.271 |
| R9 | Retained earnings to total assets ratio | 1.000 | 0.953 |
| R10 | Return on equity ratio | 1.000 | 0.406 |
| R11 | EBIT to total assets ratio | 1.000 | 0.936 |
| R12 | Net interest margin | 1.000 | 0.951 |
| R13 | Interest rate spread | 1.000 | 0.957 |
| R14 | Working capital to total assets ratio | 1.000 | 0.338 |
| R15 | Current ratio | 1.000 | 0.549 |

**Source:** Author

By default, in the procedure of PCA, each variable has a unit value of communality. Communality coefficients estimate part of the variability in each variable that is shared with others, and which is not due to measurement error or latent variable influence on the observed variable. The values in the column extraction indicate the proportion of each variable's variance that can be explained by the principal components. Variables with high values are well represented in the common factor space, while variables with low values are not well represented. The initial values can be ignored because in the PCA analysis the initial estimates for the communalities are all set to 1.

Table 3.17 lists the coefficients indicating the presence or absence of communalities in the variables.

It can be seen that the variables of the salary to assets ratio R8, the return on equity ratio R10 and the working capital to total assets ratio R14 have low correlation coefficients with other variables. However, the variables to use will be determined by PCA.

**Table 3.18: KMO and Bartlett's Test**

| | | |
|---|---|---|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | 0.635 |
| Bartlett's Test of Sphericity | Approximate Chi-Square | 2861.467 |
| | Df | 105 |
| | Sig. | 0.000 |

**Source:** Author

Table 3.18 lists the data of KMO and Bartlett's Test to verify the adequacy of sampling and the reliability of its results.

The KMO (Kaiser - Meyer - Olkin) selective adequacy measure and Bartlett's Test results are used to test the adequacy of sampling and the reliability of the result. The KMO is a measure characterizing the applicability of PCA to the sample. Kaiser (1974) interpreted the KMO test measure as follow:

> 0.9 – ‘marvelous’;
0.8 – 0.9 – ‘meritorious’;
0.7 – 0.8 – ‘middling’;
0.6 – 0.7 – ‘mediocre’;
0.5 – 0.6 – ‘miserable’ and
< 0.5 – ‘unacceptable’.

Kaiser-Meyer-Olkin’s measure of selective adequacy is a value characterizing the applicability of PCA to this sample. The value of 0.635 means satisfactory adequacy of the sample.

Bartlett’s test of sphericity is the criterion for the degree of correlation of variables. A value of p-level (Sig) less than 0.05 indicates that the data are quite acceptable for PCA because correlations between variables essentially differ from 0.

### 3.5.2 Extraction of Principal Components

The extraction of principal components is the next stage of PCA. From the mathematical point of view this has a certain analogy with the multiple regression analysis. Thus, the starting point of the study is the analysis of the obtained vector of eigenvalues of the principal components listed in Table 3.19.

**Table 3.19: Total Variance Explained (Principal Components)**

| Com-po-nent | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumula-tive % | Total | % of Variance | Cumula-tive % | Total | % of Variance | Cumula-tive % |
| 1 | 3.696 | 24.637 | 24.637 | 3.696 | 24.637 | 24.637 | 3.173 | 21.156 | 21.156 |
| 2 | 2.345 | 15.636 | 40.273 | 2.345 | 15.636 | 40.273 | 2.333 | 15.556 | 36.712 |
| 3 | 1.948 | 12.984 | 53.257 | 1.948 | 12.984 | 53.257 | 1.999 | 13.328 | 50.039 |
| 4 | 1.414 | 9.426 | 62.683 | 1.414 | 9.426 | 62.683 | 1.738 | 11.588 | 61.627 |
| 5 | 1.136 | 7.576 | 70.259 | 1.136 | 7.576 | 70.259 | 1.295 | 8.631 | 70.259 |
| 6 | 0.992 | 6.613 | 76.872 | | | | | | |
| 7 | 0.857 | 5.713 | 82.585 | | | | | | |
| 8 | 0.810 | 5.400 | 87.985 | | | | | | |
| 9 | 0.764 | 5.094 | 93.079 | | | | | | |
| 10 | 0.449 | 2.995 | 96.074 | | | | | | |
| 11 | 0.291 | 1.937 | 98.011 | | | | | | |
| 12 | 0.183 | 1.219 | 99.230 | | | | | | |
| 13 | 0.057 | 0.381 | 99.611 | | | | | | |
| 14 | 0.047 | 0.314 | 99.925 | | | | | | |
| 15 | 0.011 | 0.075 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.
**Source:** Author

Table 3.19 shows the loadings of the variables. It shows the results for 15 components as I used 15 variables.

Eigenvalues are the variances of the principal components. Because the researcher conducted principal components analysis on the correlation matrix, the variables are standardized, which means that each variable has a variance of 1, and the total variance is equal to the number of variables used in the analysis, in this case, 15. The initial eigenvalues column - the first component will always account for the most variance (and hence have the highest eigenvalue), and the next component will account for as much of the left over variance as it can, and so on. Hence, each successive component will account for less and less variance. The column '% of variance' contains the percent of variance accounted for by each principal component. Cumulative % column contains the cumulative percentage of variance accounted for by the current and all preceding principal components.

The column ‘Extraction Sums of Squared Loadings’ reproduce the values given on the same row on the left side of the table. The number of rows reproduced on the right side of the table is determined by the number of principal components whose eigenvalues are 1 or more. The last column shows the sums of squared loadings. The higher the cumulative percent that accrued towards the last component, the more consistent is the component solution. If the cumulative percent is less than 50%, it is necessary either to reduce the number of variables or to increase the number of components. In this case the cumulative percent of variance is acceptable (Satina, 2008).

With very few exceptions, not all of the extracted components are relevant for research. If the number of components is the same as that of the original variables, the PCA is meaningless since its aim is to reduce the initial set of variables. Therefore, it is necessary to select the components that should be left for further analysis. First, the use of common sense is recommended in order to retain those components which have clear theoretical or logical interpretation (Satina, 2008).

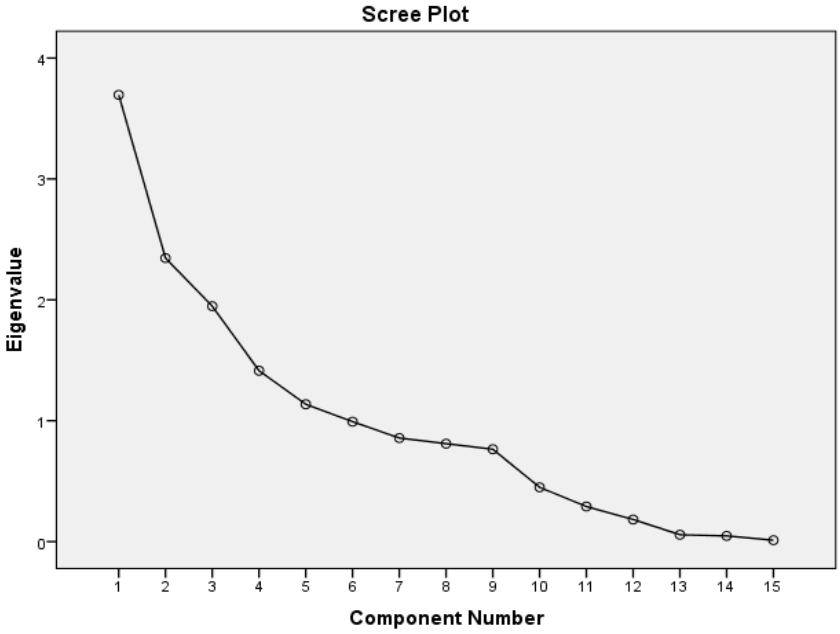
However, it is not always possible to establish the assignment of each component in advance and therefore, at the first step, formal criteria are usually used. When performing PCA with default settings, all components with eigenvalues greater than 1 are stored for further analysis. Since the number of components is equal to the number of variables, only a small number of components have eigenvalues greater than 1 which means that the command to run using the default settings gives the significant reduction in the number of variables. So the maximum amount of variance is explained with the fewest number of principal components.

There are other criteria for the selection of components including R. Cattell’s scree test (Nasledov, 2013), which allows the selection of a number of components based on the normalized simple stress plot. The plot shows eigenvalues by points in the space of two coordinates. Given that, the following rule is to retain only those components which correspond to the first points on the plot before the curve becomes flatter (Figure 3.7).

According to Kaiser’s criterion, the first five principal components should be retained as their eigenvalues exceed the threshold level of 1 (Nasledov, 2013).

The plots above also show that the variability of indicators is determined adequately by the first five principal components. In any case, a final decision on the number of components is usually taken after the interpretation of components; therefore, PCA involves the iterated selection of different numbers of components.

**Figure 3.7: Scree Plot of Data**




**Source:** Author using SPSS

Thus, for the study five principal components explaining more than 70% variance should be left.

The total contribution of the five principal components in the total variance is 70.259%. The remaining ten principal components explain less than 30% of the variance of the original attribute space.

### 3.5.3 Rotation of Principal Components to Simplify Structure

The next step after the selection of components is their rotation. This is required because the original structure of components, being mathematically correct, is generally difficult to interpret. The rotation is a simple structure to which there corresponds a high value of each variable loading for one component only and a low value for all other components. The rotation of components does not affect the mathematical rigour of the analysis; the mutual position of variables does not change on the turning of axes.

The most popular option is the rotation by the Varimax method (Satina, 2008). This is an orthogonal rotation option because, at this rotation, the axes preserve their mutual position at a right angle (Table 3.20).

To interpret the components selected for the analysis it is necessary to determine $|a_{cr}|$ usually in the range [0.6, 0.9]. The calculation of this criterion is “average of communalities” – sum the extraction of all 15 variables in Table 3.17 and divide by 15 –> 0.7022.

As can be seen from Table 3.20, the indicators R14, R8, R10 and R15 have low coefficients. R14 explains the first component by 0.524. R8 explains the first component by 0.467, R10 explains second component by 0.392 and fourth component by 0.487. Thus, these three indicators are not efficient in explaining the selected five components. They must be excluded from the analysis.

**Table 3.20: Rotated Component Matrix**

| | Component | | | | |
|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 |
| R1 | **0.859** | 0.207 | 0.082 | -0.247 | 0.234 |
| R2 | **0.856** | 0.199 | 0.025 | -0.257 | 0.247 |
| R3 | **0.737** | 0.067 | -0.229 | -0.216 | 0.024 |
| R4 | 0.058 | -0.010 | -0.054 | -0.019 | **0.759** |
| R5 | **-0.782** | 0.289 | -0.138 | 0.079 | -0.087 |
| R6 | -0.122 | -0.323 | -0.067 | **0.833** | -0.022 |
| R7 | -0.040 | 0.135 | -0.071 | **0.746** | 0.059 |
| R8 | 0.467 | -0.105 | 0.188 | 0.070 | -0.009 |
| R9 | 0.070 | **0.970** | 0.058 | -0.049 | 0.018 |
| R10 | -0.090 | 0.392 | -0.040 | 0.487 | -0.078 |
| R11 | -0.041 | **0.963** | 0.065 | 0.059 | -0.009 |
| R12 | 0.111 | 0.053 | **0.967** | -0.037 | -0.019 |
| R13 | 0.052 | 0.063 | **0.964** | -0.136 | -0.054 |
| R14 | 0.524 | 0.001 | 0.027 | 0.195 | -0.172 |
| R15 | 0.063 | -0.007 | -0.004 | 0.023 | **0.743** |

Values that are higher than critical value at 0.7022 are marked in bold type
Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in five iterations.

**Source:** Author

The indicators after the exclusion are not examined. For that to be achieved it is necessary to iterate PCA but without these three indicators (Table 3.21). Thus, 12 indicators out of 15 are used.

Without the three indicators, the degree of explanation of the variance has risen to 83 per cent, i.e., the model quality has improved.

**Table 3.21: Total Variance Explained (without the three excluded coefficients)**

| Com-po-Nent | Initial Eigenvalues | | | Extraction Sums of Squared Loadings | | | Rotation Sums of Squared Loadings | | |
|---|---|---|---|---|---|---|---|---|---|
| | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % | Total | % of Variance | Cumulative % |
| 1 | 3.449 | 28.743 | 28.743 | 3.449 | 28.743 | 28.743 | 3.029 | 25.238 | 25.238 |
| 2 | 2.225 | 18.545 | 47.288 | 2.225 | 18.545 | 47.288 | 2.207 | 18.391 | 43.629 |
| 3 | 1.901 | 15.839 | 63.127 | 1.901 | 15.839 | 63.127 | 2.003 | 16.691 | 60.320 |
| 4 | 1.290 | 10.747 | 73.873 | 1.290 | 10.747 | 73.873 | 1.497 | 12.473 | 72.793 |
| 5 | 1.109 | 9.238 | 83.111 | 1.109 | 9.238 | 83.111 | 1.238 | 10.318 | 83.111 |
| 6 | 0.798 | 6.648 | 89.759 | | | | | | |
| 7 | 0.478 | 3.984 | 93.743 | | | | | | |
| 8 | 0.392 | 3.266 | 97.009 | | | | | | |
| 9 | 0.241 | 2.007 | 99.016 | | | | | | |
| 10 | 0.058 | 0.480 | 99.496 | | | | | | |
| 11 | 0.049 | 0.410 | 99.906 | | | | | | |
| 12 | 0.011 | 0.094 | 100.000 | | | | | | |

Extraction Method: Principal Component Analysis.

**Source:** Author

The rotated matrix of component loadings on the 12 remaining indicators has also changed. The titles of indicators and their interpretation are added in Table 3.22.

**Table 3.22: Rotated Component Matrix and Interpretation**

| Component | Indicator Deciphering | | Component | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1 | 2 | 3 | 4 | 5 |
| Capital adequacy | R1 | Capital to assets | 0.922 | 0.183 | 0.131 | -0.093 | 0.155 |
| | R2 | Regulatory capital to risk-weighted assets | 0.924 | 0.179 | 0.073 | -0.098 | 0.166 |
| | R3 | Regulatory Tier 1 capital to risk-weighted assets | 0.787 | 0.023 | -0.179 | -0.118 | -0.027 |
| | R5 | Debt to equity | -0.789 | 0.371 | -0.187 | 0.041 | -0.041 |
| Return on assets | R9 | Return on assets (ROA) | 0.118 | 0.967 | 0.062 | -0.048 | -0.005 |
| | R11 | Earnings before interest and tax to total assets | -0.020 | 0.956 | 0.058 | 0.012 | -0.013 |
| Profitability | R12 | Net interest margin | 0.080 | 0.049 | 0.979 | -0.006 | -0.030 |
| | R13 | Interest rate spread | 0.015 | 0.061 | 0.968 | -0.131 | -0.048 |
| Asset quality (NPL) | R6 | Nonperforming loans net of provisions to total gross loans | -0.206 | -0.321 | -0.071 | 0.811 | -0.036 |
| | R7 | Nonperforming loans net of provisions to capital | -0.072 | 0.210 | -0.069 | 0.886 | 0.000 |
| Liquidity and leverage | R4 | Equity to debt | 0.097 | -0.014 | -0.050 | -0.019 | 0.765 |
| | R15 | Current liquidity | 0.072 | -0.002 | -0.011 | -0.006 | 0.771 |

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
Rotation converged in 5 iterations.

**Source:** Author

Following Safdari, Scannell and Ohanian (2005), Satina (2008) and Othman (2013), PCA was employed in the current study. Safdari et al. (2005) obtained 2 components, while Satina (2008) obtained 4 components and Othman (2013) obtained 3 components. In this study, based on PCA results, 12 indicators out of 15 were isolated. They reflect on 5 categories: Capital adequacy, Return on assets, Profitability, Asset quality (NPL) and Liquidity and leverage.

### 3.5.4 Interpretation of Principal Components

The following conclusions can be drawn from the analysis of component loading matrices (Satina, 2008):

1. The first generalized component following the results of the calculation is most closely related to the four indicators; R1 is the capital to assets ratio, R2 is the regulatory capital to risk-weighted assets ratio, R3 is the regulatory Tier 1 capital to risk-weighted assets ratio and R5 is the debt to equity ratio.

$$Coefficient\ of\ Interpretation = \frac{\alpha_{11}^2+\alpha_{21}^2+\alpha_{31}^2+\alpha_{41}^2}{\sum_{j=1}^{8}\alpha_{j1}^2}100\% = 97.3\%$$

Thus, the four original attributes explain more than 97% of the variance of the first component.

2. The second generalized component can be titled the return on assets as it is most closely related to R9 as the ratio of the return on assets (ROA) and R11 as the ratio of the earnings before interest and taxes to total assets.

$$Coefficient\ of\ Interpretation = \frac{\alpha_{52}^2+\alpha_{62}^2}{\sum_{j=1}^{8}\alpha_{j2}^2}100\% = 83.8\%$$

Thus, these indicators explain nearly 84% of the variance of the second component.

3. The third component is explained by the indicators R12 as the net interest margin and R13 as the interest rate spread.

$$Coefficient\ of\ Interpretation = \frac{\alpha_{73}^2+\alpha_{83}^2}{\sum_{j=1}^{8}\alpha_{j3}^2}100\% = 94.6\%$$

Hence, the two original attributes explain more than 94.6% of the variance of the second component.

4. The fourth generalized component is most closely related to R7 as the ratio of non-performing loans net of provisions to capital and to R6 as the ratio of non-performing loans net of provisions to total loans.

$$Coefficient\ of Interpretation = \frac{\alpha_{94}^2 + \alpha_{104}^2}{\sum_{j=1}^{8} \alpha_{j4}^2} 100\% = 96.4\%$$

The two original attributes explain more than 96% of the variance of the fourth component.

5. The fifth component is most closely related to R4 as the ratio of total equity to debt and to R15 as the current liquidity ratio.

$$Coefficient\ of\ Interpretation = \frac{\alpha_{115}^2 + \alpha_{125}^2}{\sum_{j=1}^{8} \alpha_{j5}^2} 100\% = 95.3\%$$

These two indicators explain more than 95% of the variance of the fifth component.

### 3.6 Results: Clustering of Banking Sector by Extent of Financial Soundness

In the previous step, five components described by twelve indicators are produced using PCA. The next step of the cluster-based methodology of assessment of financial soundness at the macro level is to conduct a cluster analysis, which identifies clusters and calculates mean values of financial ratios for interpretation of the results.

Clustering is the splitting of aggregate objects, each of which is described by a set of variables, into a number of similar classes in a sense. After selecting the attributes, the method of representation of their weights in documents and the units of measure and information about each attribute of any object is set out in a table where the set of rows are individuals (objects) and the set of columns are attributes (descriptors). Clustering is a type of classification determined by a final set of objects. The relationship between the classified objects is presented as the proximity matrix with rows and columns that correspond to the objects (Berkhin, 2002).

The principal components that have been calculated by PCA characterizing the financial soundness of banks were used as clustering variables.

#### 3.6.1 Rank the Kazakhstan Banks

Preliminarily, as verification of clustering results, a universal ranking system proposed by Al-Osaimy (2004) and Othman (2013) will be used. This system ranks the banks by their financial performances. In addition, according to Khotinskaya (2015), ranking is characterized by objectivity, independence of results and the ability to rank data on the ranking criterion: five principal components were used to compose the summary ranking score:

Capital adequacy
Return on assets
Profitability
Asset quality (NPL)
Liquidity and leverage

In line with Al-Osaimi (2004) and Othman (2013), this study classifies the ranks from 1 to 10 (where “1” indicates the worst while “10” presents the best). Rankings wereassigned to each of the twelve financial ratios, then an overall average ranking for each bank was then calculated on 1 January, 2008 and 1 January, 2014 (Appendix D-M).

For each financial ratio, the smallest and largest values were taken and the difference between these values was divided into 10 equal ranges. In accordance with the range in which the value of the ratio of an individual bank falls into the corresponding score granted from 1 to 10. The worst value is assigned with value of 1, and 10 for the best. For R1 Capital to assets, R2 Regulatory capital to risk-weighted assets, R3 Regulatory Tier 1 capital to Risk-weighted assets, R4 Equity to debt, R9 Return on assets (ROA), R11 Earnings before interest and taxes to assets, R12 Net interest margin, R13 Interest rate spread, R15 Current liquidity ratio.  The best value is the highest value and the worst is the smallest. Whereas for R5 Debt to equity, R6 NPL to total gross loans, R7 NPL to capital, the best value is the smallest and the worst value is the largest.

The ranking of Kazakhstan banks in 2008 and 2014 is presented in the following tables 3.23 and 3.24.

**Table 2.23: The Ranking Scores of Banks, 1st January, 2008**

| Banks | Capital Adequacy | | | | Return on Assets | | Profitability | | Assets Quality | | Liquidity and Leverage | | Total Score | Average Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 | | |
| Masterbank | 10 | 10 | 3 | 10 | 8 | 1 | 3 | 4 | 10 | 10 | 10 | 10 | 89 | 7.42 |
| SB Bank of China in Kazakhstan | 5 | 4 | 4 | 9 | 10 | 5 | 10 | 10 | 10 | 10 | 1 | 1 | 79 | 6.58 |
| Senim-Bank | 7 | 7 | 2 | 10 | 10 | 3 | 7 | 8 | 10 | 10 | 1 | 1 | 76 | 6.33 |
| SB Lariba-Bank | 6 | 4 | 2 | 10 | 10 | 4 | 9 | 9 | 10 | 10 | 1 | 1 | 76 | 6.33 |
| Zaman-Bank | 10 | 10 | 2 | 10 | 10 | 3 | 6 | 7 | 7 | 7 | 1 | 1 | 74 | 6.17 |
| TPBK | 3 | 3 | 10 | 8 | 10 | 3 | 7 | 8 | 10 | 10 | 1 | 1 | 74 | 6.17 |
| Express Bank | 9 | 9 | 2 | 10 | 1 | 3 | 6 | 7 | 10 | 10 | 1 | 1 | 69 | 5.75 |
| SB NB of Pakistan in Kazakhstan | 8 | 8 | 2 | 10 | 9 | 1 | 2 | 4 | 10 | 10 | 1 | 1 | 66 | 5.50 |
| SB Alfa-Bank | 2 | 2 | 1 | 7 | 10 | 4 | 9 | 10 | 10 | 9 | 1 | 1 | 66 | 5.50 |
| SB Taib Kazakh Bank | 6 | 6 | 3 | 10 | 9 | 1 | 3 | 4 | 10 | 10 | 1 | 1 | 64 | 5.33 |
| Kazinkombank | 9 | 7 | 2 | 10 | 9 | 1 | 1 | 2 | 10 | 10 | 1 | 1 | 63 | 5.25 |
| SB Sberbank of Russia | 6 | 5 | 1 | 10 | 9 | 3 | 5 | 6 | 8 | 8 | 1 | 1 | 63 | 5.25 |
| Delta Bank | 4 | 3 | 1 | 8 | 9 | 3 | 6 | 7 | 10 | 9 | 1 | 1 | 62 | 5.17 |
| Eximbank Kazakhstan | 3 | 3 | 1 | 8 | 9 | 3 | 6 | 7 | 10 | 10 | 1 | 1 | 62 | 5.17 |
| Metrokombank | 6 | 6 | 2 | 10 | 9 | 1 | 1 | 3 | 10 | 10 | 1 | 1 | 60 | 5.00 |
| MB Alma-Ata | 3 | 3 | 1 | 8 | 10 | 10 | 10 | 10 | 1 | 1 | 1 | 1 | 59 | 4.92 |
| Alliance Bank | 1 | 1 | 1 | 4 | 9 | 4 | 9 | 10 | 10 | 7 | 1 | 1 | 58 | 4.83 |
| Kazinvestbank | 2 | 1 | 1 | 5 | 9 | 3 | 7 | 8 | 10 | 10 | 1 | 1 | 58 | 4.83 |
| SB KZI bank | 3 | 3 | 1 | 8 | 9 | 2 | 3 | 5 | 10 | 10 | 1 | 1 | 56 | 4.67 |
| Demir Kazakhstan Bank | 3 | 3 | 1 | 8 | 9 | 2 | 3 | 5 | 10 | 10 | 1 | 1 | 56 | 4.67 |
| Danabank | 4 | 4 | 1 | 8 | 9 | 2 | 4 | 5 | 9 | 7 | 1 | 1 | 55 | 4.58 |
| Bank Turanalem | 1 | 1 | 1 | 5 | 9 | 3 | 6 | 7 | 10 | 9 | 1 | 1 | 54 | 4.50 |

| Banks | Capital Adequacy | | | | Return on Assets | | Profitability | | Assets Quality | | Liquidity and Leverage | | Total Score | Average Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 | | |
| Nurbank | 2 | 2 | 1 | 6 | 9 | 3 | 6 | 7 | 9 | 6 | 1 | 1 | 53 | 4.42 |
| DO Temirbank | 1 | 1 | 1 | 4 | 9 | 4 | 9 | 10 | 9 | 3 | 1 | 1 | 53 | 4.42 |
| SB ABN Amro Bank | 1 | 1 | 1 | 4 | 9 | 2 | 5 | 6 | 10 | 10 | 1 | 1 | 51 | 4.25 |
| Bank CenterCredit | 1 | 1 | 1 | 1 | 9 | 3 | 7 | 8 | 10 | 7 | 1 | 1 | 50 | 4.17 |
| Eurasian Bank | 1 | 1 | 1 | 3 | 9 | 3 | 6 | 7 | 10 | 7 | 1 | 1 | 50 | 4.17 |
| Citibank Kazakhstan | 1 | 1 | 1 | 3 | 9 | 3 | 6 | 7 | 9 | 7 | 1 | 1 | 49 | 4.08 |
| Tsesnabank | 1 | 1 | 1 | 4 | 8 | 3 | 6 | 7 | 10 | 6 | 1 | 1 | 49 | 4.08 |
| SB HSBC Bank of Kazakhstan | 1 | 1 | 1 | 1 | 9 | 2 | 5 | 6 | 10 | 10 | 1 | 1 | 48 | 4.00 |
| ATF Bank | 1 | 1 | 1 | 2 | 8 | 3 | 5 | 6 | 10 | 7 | 1 | 1 | 46 | 3.83 |
| Halyk Bank of Kazakhstan | 1 | 1 | 1 | 1 | 9 | 3 | 7 | 7 | 10 | 4 | 1 | 1 | 46 | 3.83 |
| Bank Caspian | 1 | 1 | 1 | 3 | 9 | 3 | 7 | 8 | 9 | 1 | 1 | 1 | 45 | 3.75 |
| Kazkommertsbank | 1 | 1 | 1 | 2 | 9 | 3 | 6 | 7 | 9 | 3 | 1 | 1 | 44 | 3.67 |

**Source: Author**

**Table 3.24: The Ranking Scores of Banks, 1st January, 2014**

| Banks | Capital Adequacy | | | | Return on Assets | | Profitability | | Assets Quality | | Liquidity and Leverage | | Total Score | Average Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 | | |
| SB PNB Kazakhstan | 10 | 10 | 10 | 10 | 6 | 4 | 2 | 2 | 9 | 10 | 10 | 10 | 93 | 7.75 |
| SB NB of Pakistan in Kazakhstan | 10 | 10 | 7 | 10 | 8 | 6 | 4 | 4 | 8 | 10 | 4 | 10 | 91 | 7.58 |
| Zaman Bank | 9 | 10 | 8 | 10 | 7 | 5 | 2 | 3 | 10 | 10 | 4 | 7 | 85 | 7.08 |
| SB KZI Bank | 8 | 8 | 6 | 10 | 8 | 7 | 3 | 4 | 10 | 10 | 1 | 4 | 79 | 6.58 |
| Islamic Bank Al Hilal | 8 | 8 | 9 | 10 | 7 | 4 | 2 | 3 | 10 | 10 | 4 | 4 | 79 | 6.58 |
| Shinhan Bank Kazakhstan | 8 | 8 | 10 | 10 | 7 | 5 | 2 | 3 | 10 | 10 | 2 | 4 | 79 | 6.58 |
| Home Credit Bank | 2 | 1 | 1 | 7 | 10 | 7 | 10 | 10 | 10 | 10 | 5 | 1 | 74 | 6.17 |
| Bank Positive Kazakhstan | 6 | 6 | 4 | 10 | 6 | 5 | 3 | 4 | 10 | 10 | 1 | 2 | 67 | 5.58 |
| SB Taib Kazakh Bank | 6 | 6 | 5 | 10 | 7 | 4 | 2 | 3 | 10 | 10 | 2 | 2 | 67 | 5.58 |
| SB RBS | 4 | 4 | 4 | 8 | 7 | 5 | 1 | 2 | 10 | 10 | 2 | 1 | 58 | 4.83 |
| Bank Kassa Nova | 2 | 1 | 1 | 6 | 7 | 7 | 3 | 4 | 10 | 10 | 6 | 1 | 58 | 4.83 |
| Eximbank Kazakhstan | 3 | 3 | 2 | 8 | 6 | 6 | 3 | 4 | 10 | 10 | 1 | 1 | 57 | 4.75 |
| ForteBank | 3 | 3 | 3 | 8 | 7 | 5 | 2 | 3 | 10 | 10 | 1 | 1 | 56 | 4.67 |
| AsiaCredit Bank | 2 | 2 | 2 | 7 | 7 | 8 | 2 | 4 | 10 | 10 | 1 | 1 | 56 | 4.67 |
| Kaspi Bank | 1 | 1 | 1 | 3 | 8 | 9 | 3 | 4 | 9 | 10 | 3 | 1 | 53 | 4.42 |
| Delta Bank | 1 | 1 | 1 | 3 | 7 | 8 | 3 | 4 | 10 | 10 | 3 | 1 | 52 | 4.33 |
| TPBK | 2 | 3 | 3 | 7 | 6 | 4 | 1 | 2 | 10 | 10 | 1 | 1 | 50 | 4.17 |
| Bank Astana-Finance | 1 | 2 | 2 | 5 | 6 | 6 | 2 | 4 | 10 | 10 | 1 | 1 | 50 | 4.17 |
| SB Alpha Bank | 1 | 1 | 1 | 5 | 7 | 8 | 2 | 3 | 10 | 10 | 1 | 1 | 50 | 4.17 |
| SB Bank of China | 1 | 2 | 5 | 5 | 7 | 5 | 1 | 2 | 10 | 10 | 1 | 1 | 50 | 4.17 |
| Eurasian Bank" | 1 | 1 | 1 | 4 | 7 | 8 | 3 | 4 | 9 | 10 | 1 | 1 | 50 | 4.17 |
| SB Sberbank | 1 | 1 | 1 | 3 | 7 | 10 | 2 | 3 | 10 | 10 | 1 | 1 | 50 | 4.17 |
| Kazkommertsbank | 2 | 1 | 1 | 6 | 7 | 7 | 3 | 3 | 7 | 10 | 1 | 1 | 49 | 4.08 |
| Halyk Bank of Kazakhstan | 1 | 1 | 1 | 5 | 8 | 6 | 2 | 3 | 9 | 10 | 1 | 1 | 48 | 4.00 |

| Banks | Capital Adequacy | | | | Return on Assets | | Profitability | | Assets Quality | | Liquidity and Leverage | | Total Score | Average Score |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 | | |
| Citibank Kazakhstan | 1 | 2 | 2 | 5 | 7 | 6 | 1 | 2 | 10 | 10 | 1 | 1 | 48 | 4.00 |
| SB HSBC Bank Kazakhstan | 1 | 1 | 2 | 4 | 7 | 6 | 1 | 3 | 10 | 10 | 1 | 1 | 47 | 3.92 |
| VTB Bank Kazakhstan | 1 | 1 | 1 | 3 | 6 | 6 | 3 | 4 | 10 | 10 | 1 | 1 | 47 | 3.92 |
| Qazaq Banki | 1 | 1 | 1 | 2 | 6 | 9 | 2 | 3 | 10 | 10 | 1 | 1 | 47 | 3.92 |
| Bank RBK | 1 | 1 | 1 | 1 | 6 | 8 | 2 | 4 | 10 | 10 | 1 | 1 | 46 | 3.83 |
| Tsesnabank | 1 | 1 | 1 | 1 | 7 | 7 | 2 | 4 | 10 | 10 | 1 | 1 | 46 | 3.83 |
| Bank CenterCredit | 1 | 1 | 1 | 4 | 6 | 6 | 2 | 3 | 9 | 10 | 1 | 1 | 45 | 3.75 |
| Kazinvestbank | 1 | 1 | 1 | 3 | 6 | 7 | 2 | 3 | 9 | 10 | 1 | 1 | 45 | 3.75 |
| Temirbank | 1 | 1 | 1 | 4 | 6 | 6 | 2 | 2 | 6 | 10 | 2 | 1 | 42 | 3.50 |
| BTA Bank | 1 | 2 | 2 | 5 | 7 | 7 | 2 | 1 | 1 | 8 | 2 | 1 | 39 | 3.25 |
| ATF Bank | 1 | 1 | 1 | 1 | 6 | 6 | 1 | 2 | 6 | 9 | 2 | 1 | 37 | 3.08 |
| Nurbank | 2 | 2 | 2 | 6 | 1 | 1 | 1 | 2 | 7 | 10 | 1 | 1 | 36 | 3.00 |
| Alliance Bank | 1 | 1 | 1 | 1 | 6 | 9 | 1 | 1 | 5 | 1 | 2 | 1 | 30 | 2.50 |

**Source:** Author

The universal ranking results will be compared with the interpreted results of Cluster Based Methodology in Section 3.7.2

### 3.6.2 Clustering of the Banking Sector, 1st January, 2008

From the results of clustering banks on 1st January 2008, the following clusters were obtained for the five principal components (Table 3.25):

**Table 3.25: Cluster Membership of Banks, 1st January, 2008**

| Cluster | Banks | Distance |
|---|---|---|
| I | Metrokombank | 0.355 |
| | Express Bank | 0.607 |
| | SB Taib Kazakh Bank | 0.096 |
| | SB Bank of China in Kazakhstan | 0.531 |
| | SB "NB of Pakistan" in Kazakhstan | 0.275 |
| | Zaman-Bank | 0.707 |
| | Kazinkombank | 0.595 |
| | SB Lariba-Bank | 0.446 |
| | Senim-Bank | 0.208 |
| | SB Sberbank of Russia | 0.479 |
| II | Delta Bank | 0.153 |
| | Danabank | 0.268 |
| | SB Alfa-Bank | 0.335 |
| | SB KZI bank | 0.266 |
| | Demir Kazakhstan Bank | 0.184 |
| | MB Alma-Ata | 0.903 |
| | Eximbank Kazakhstan | 0.195 |
| III | Alliance Bank | 0.391 |
| | ATF Bank | 0.234 |
| | Bank Caspian | 0.752 |
| | Bank Turanalem | 0.181 |
| | Bank CenterCredit | 0.269 |
| | SJ SB ABN Amro Bank | 0.240 |
| | Eurasian Bank | 0.060 |
| | Kazinvestbank | 0.332 |
| | Kazkommertsbank | 0.154 |
| | Halyk Bank of Kazakhstan | 0.338 |
| | Nurbank | 0.477 |
| | Citibank Kazakhstan | 0.191 |
| | Tsesnabank | 0.086 |
| | SB HSBC Bank of Kazakhstan | 0.433 |
| | DO Temirbank | 0.266 |

Without Masterbank and TPBK

**Source:** Author

When clustering the banks by the five principal components (Table 3.25), two banks were identified and eliminated from analysis: namely, Masterbank and TPBK, because they had abnormal levels of analyzed indicators. In 2008 Masterbank was new and its capital adequacy ratios were abnormally high, especially its equity to debt ratio at 548 and its current liquidity ratio at 986. TPBK has high capital adequacy ratios with very low liquidity and interest income that at times distinguished it from all other banks (Table 3.26).

Initially, the researcher divided banks into three clusters by k-means method. For detailed analysis of the three clusters of financial soundness characterizing the banking system, the above data should be presented in terms of the median of indicators of the obtained bank clusters (Table 3.26).

**Table 3.26: Median Values of Financial Soundness Indicators of Obtained Clusters, 1st January, 2008**

| Component | | Component 1 | | | | Component 2 | | Component 3 | | Component 4 | | Component 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | Number of banks | Capital adequacy | Regulatory capital to risk-weighted assets | Regulatory Tier 1 capital to risk-weighted assets | Debt to equity | Return on assets | EBIT to assets | Net interest rate margin | Interest rate spread | NPL to total gross loans | NPL to capital | Current liquidity | Equity to debt |
| | | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 |
| 1 | 10 | 0.666 | 0.636 | 0.806 | 0.503 | 0.022 | 0.048 | 0.051 | 0.035 | 0.000 | 0.000 | 1.3805 | 2.023 |
| 2 | 7 | 0.329 | 0.278 | 0.330 | 2.035 | 0.023 | 0.052 | 0.036 | 0.031 | 0.013 | 0.025 | 0.744 | 0.491 |
| 3 | 15 | 0.154 | 0.095 | 0.142 | 5.719 | 0.017 | 0.053 | 0.025 | 0.022 | 0.015 | 0.063 | 1.35 | 0.175 |
| TPBK* | | 0.371 | 0.325 | 3.872 | 1.692 | 0.046 | 0.062 | 0.024 | 0.023 | 0.000 | 0.000 | 0.938 | 0.591 |
| Masterbank* | | 0.998 | 0.989 | 1.058 | 0.002 | 0.008 | 0.026 | 0.036 | | 0.000 | 0.000 | 986.38 | 549 |

***** TPBK and Masterbank are not included in the cluster analysis as stated above
**Source:** Author

Medean values of financial soundness indicators allow isolation of three clusters with close rates of capital adequacy, return on assets, profitability, NPL, liquidity and leverage. As shown in Table 3.26, all banks show a low return on assets. The asset quality problem in this period has not yet worsened and the average level of non-performing loans in the banking sector of Kazakhstan does not exceed 4%.

### 3.6.3 Clustering of Banking Sector, 1st January, 2014

As of 1st January, 2014 the cluster analysis was performed for 37 banks of Kazakhstan. Similar to the process described in section 3.6.2, the clustering variables used were the five principal components characterizing the financial soundness of banks previously calculated based on PCA.

The clustering was undertaken to obtain the final division into three clusters. The results of final clustering on 1st January, 2014 are as follows (Table 3.27).

**Table 3.27: Cluster Distribution of Banks,1st January, 2014**

| Cluster | Banks | Distance |
|---|---|---|
| I | Bank Positive Kazakhstan | 0.639 |
| | SB PNB Kazakhstan | 0.835 |
| | SB KZI Bank" | 0.464 |
| | Zaman Bank | 0.361 |
| | Islamic Bank Al Hilal | 0.364 |
| | Shinhan Bank Kazakhstan | 0.417 |
| | SB Taib Kazakh Bank | 0.655 |
| | SB NB of Pakistan in Kazakhstan | 0.888 |
| II | AsiaCredit Bank | 0.340 |
| | Bank RBK | 0.644 |
| | Delta Bank | 0.576 |
| | ForteBank | 0.755 |
| | Kaspi Bank | 0.830 |
| | Qazaq Banki | 0.572 |
| | Bank Astana-Finance | 0.244 |
| | Bank Kassa Nova | 0.524 |
| | Bank CenterCredit | 0.835 |
| | SB Alpha Bank | 0.252 |
| | Eurasian Bank" | 0.673 |
| | Kazinvestbank | 0.550 |
| | Halyk Bank of Kazakhstan | 0.585 |
| | Citibank Kazakhstan | 0.750 |
| | TPBK | 0.864 |
| | Tsesnabank | 0.570 |
| | Eximbank Kazakhstan | 0.682 |
| | SB RBS (Kazakhstan) | 1.065 |
| | SB Bank of China | 0.847 |
| | SB HSBC Bank Kazakhstan | 0.261 |
| | SB Sberbank | 0.441 |
| | VTB Bank (Kazakhstan) | 0.385 |
| III | Kazkommertsbank | 0.626 |
| | Nurbank | 0.626 |
| | ATF Bank | 0.479 |
| | Temirbank | 0.479 |

Without Zhilstroysberbank

**Source:** Author

Before clustering, three banks were removed from the data base because of their abnormal indicators (Appendix 3A Alliance Bank, BTA Bank, Home Credit Bank) to remove outliers and to improve classification. Alliance Bank and BTA Bank have enormous levels of R7 NPL to capital at 29 and 8.513 respectively. Home Credit Bank has three abnormally high indicators: of R12 Net interest rate margin at 0.269, R13 Interest rate spread at 0.214 and R15 Current liquidity ratio at 3.833. SB Home Credit Bank specializes in consumer credit. It has an extensive retail network and its main clients are private persons to which it provides consumer loans. Its net interest rate margin and interest rate spread exceed significantly the indicators of other banks at 26.9% and 21.4%. This bank stands apart from the rest owing to its very high interest rate spread and net interest margin.

Again, the researcher divided banks for three clusters by thek-means method and presented the medians of indicators of the obtained bank clusters (Table 3.28).

**Table 3.28: Median Values of Financial Soundness Indicators of the Obtained Clusters, 1st January, 2014**

| Component | | Component 1 | | | | Component 2 | | Component 3 | | Component 4 | | Component 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | Number of banks | Capital adequacy | Regulatory capital to risk-weighted assets | Regulatory Tier 1 capital to risk-weighted assets | Debt to equity | Return on assets | EBIT to assets | Net interest rate margin | Interest rate spread | NPL to total gross loans | NPL to capital | Current liquidity | Equity to debt |
| | | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 |
| 1 | 8 | 0.657 | 0.619 | 0.866 | 0.524 | 0.018 | 0.023 | 0.061 | 0.050 | 0.045 | 0.048 | 2.054 | 1.920 |
| 2 | 22 | 0.145 | 0.110 | 0.147 | 5.943 | 0.019 | 0.063 | 0.056 | 0.048 | 0.034 | 0.174 | 0.850 | 0.169 |
| 3 | 4 | 0.158 | 0.107 | 0.124 | 5.397 | 0.001 | 0.053 | 0.041 | 0.015 | 0.348 | 1.832 | 1.090 | 0.188 |
| Alliance Bank* | | 0.103 | 0.075 | 0.109 | 8.685 | 0.005 | 0.116 | 0.022 | -0.006 | 0.498 | 29.001 | 1.104 | 0.115 |
| BTA bank* | | 0.156 | 0.141 | 0.250 | 5.394 | 0.018 | 0.079 | 0.057 | -0.020 | 0.849 | 8.513 | 1.448 | 0.185 |
| SB Home Credit Bank* | | 0.240 | 0.131 | 0.162 | 3.163 | 0.105 | 0.076 | 0.269 | 0.214 | 0.021 | 0.146 | 3.833 | 0.316 |

***** Alliance Bank, BTA Bank and SB Home Credit Bank are not included in the cluster analysis as stated above

**Source:** Author

As can be seen from Table 3.27 on 1st January, 2014, all the banks apart from the first cluster have low rates of capital adequacy. The first cluster has a high level of capital adequacy, a low NPL and liquidity and the highest profitability. The second cluster has low capital adequacy, the highest return on assets and the lowest NPL. The third cluster has low capital adequacy and profitability with an abnormal level of NPL.

The median values of financial soundness indicators allow the isolation of three clusters with close rates of capital adequacy, return on assets, profitability, NPL, liquidity and leverage. In general, capital adequacy decreased on 1st January, 2014 while the NPL level dramatically increased.

### 3.7 Interpretation of Clusterization Results

The final step of the cluster based methodology of the assessment of financial soundness banking sector is the interpretation of the results. This step includes two parts of the final grouping of clusters using limits of financial soundness and the interpretation of the structure of the banking sector by the degree of financial soundness.

#### 3.7.1 Final Grouping of Clusters Using Limits of Financial Soundness

The results of clustering should be related to the limits of financial soundness at Step 2 of the cluster based methodology of the assessment of banking sector financial soundness. For the interpretation of clustering results, the mean values of the financial soundness indicators of clusters obtained above correspond with the limits of financial soundness. Each cell of the table has a definite colour while a red shading indicates a value in the 1st quartile of “Unsound Banks”, a yellow shading shows values of the 2nd quartile “Risky Banks” and a green shading shows the rest as “Sound Banks”. The further distribution of clusters into groups performed according to the principle of colour predominance and the special status of the red colour.

In Table 3.29 the median values with the limits of financial soundness are represented on 1st January, 2008.

**Table 3.29: Median Values Distributed by Limits of Financial Soundness, 1st January, 2008**

| Compo-nent | | Component 1 | | | | Component 2 | | Component 3 | | Component 4 | | Component 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | Number of banks | Capital adequacy | Regulatory capital to risk-weighted assets | Regulatory Tier 1 capital to risk-weighted assets | Debt to equity | Return on assets | EBIT to assets | Net interest rate margin | Interest rate spread | NPL to total gross loans | NPL to capital | Current liquidity | Equity to debt |
| | | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 |
| 1 | 10 | 0.666 | 0.636 | 0.806 | 0.503 | 0.022 | 0.048 | 0.051 | 0.035 | 0.000 | 0.000 | 1.3805 | 2.023 |
| 2 | 7 | 0.329 | 0.278 | 0.330 | 2.035 | 0.023 | 0.052 | 0.036 | 0.031 | 0.013 | 0.025 | 0.744 | 0.491 |
| 3 | 15 | 0.154 | 0.095 | 0.142 | 5.719 | 0.017 | 0.053 | 0.025 | 0.022 | 0.015 | 0.063 | 1.35 | 0.175 |
| TPBK* | | 0.371 | 0.325 | 3.872 | 1.692 | 0.046 | 0.062 | 0.024 | 0.023 | 0.000 | 0.000 | 0.938 | 0.591 |
| Master-bank* | | 0.998 | 0.989 | 1.058 | 0.002 | 0.008 | 0.026 | 0.036 | | 0.000 | 0.000 | 986.38 | 549 |

**Source:** Author

**The first cluster** of Table 3.28 has 2 yellow and 10 green indicators. All banks of this cluster are within the sound group.

**The second cluster** has 1 red 2 yellow and 9 green indicators; therefore, all banks of this cluster also correspond to the group of sound banks.

**The third cluster** has 3 red, 4 yellow and 5 green indicators. According to the principle of colour predominance and the red colour rule all banks of this cluster are classified as a group of risky banks.

TPBK and Masterbank were earlier excluded from the analysis because of the abnormal levels of their indicators analysed and distributed into their appropriate group. TPBK has 1 red, 2 yellow and 9 green indicators and therefore the bank is considered to be in the first group of sound banks. Masterbank has 1 red, 3 yellow and 8 green indicators and according to the principle of colour predominance, the bank is included in the first group of sound banks.

A similar corresponding of median values with the limits of financial soundness on 1st January, 2014 is presented in Table 3.30

**Table 3.30: Median Values Distributed by Limits of Financial Soundness, 1st January, 2014**

| Component | | Component 1 | | | | Component 2 | | Component 3 | | Component 4 | | Component 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Cluster | Number of banks | Capital adequacy | Regulatory capital to risk-weighted assets | Regulatory Tier 1 capital to risk-weighted assets | Debt to equity | Return on assets | EBIT to assets | Net interest rate margin | Interest rate spread | NPL to total gross loans | NPL to capital | Current liquidity | Equity to debt |
| | | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 |
| 1 | 8 | 0.657 | 0.619 | 0.866 | 0.524 | 0.018 | 0.023 | 0.061 | 0.050 | 0.045 | 0.048 | 2.054 | 1.920 |
| 2 | 22 | 0.145 | 0.110 | 0.147 | 5.943 | 0.019 | 0.063 | 0.056 | 0.048 | 0.034 | 0.174 | 0.850 | 0.169 |
| 3 | 4 | 0.158 | 0.107 | 0.124 | 5.397 | 0.001 | 0.053 | 0.041 | 0.015 | 0.348 | 1.832 | 1.090 | 0.188 |
| Alliance Bank* | | 0.103 | 0.075 | 0.109 | 8.685 | 0.005 | 0.116 | 0.022 | -0.006 | 0.498 | 29.00 | 1.104 | 1.104 |
| BTA bank* | | 0.156 | 0.141 | 0.250 | 5.394 | 0.018 | 0.079 | 0.057 | -0.020 | 0.849 | 8.513 | 1.448 | 1.448 |
| SB Home Credit Bank* | | 0.240 | 0.131 | 0.162 | 3.163 | 0.105 | 0.076 | 0.269 | 0.214 | 0.021 | 0.146 | 3.833 | 3.833 |

**Source:** Author

**The first cluster** has 2 red and 10 green indicators and according all banks of this cluster are classified as a sound group.

**The second cluster** has 2 red, 6 yellow and 4 green indicators and thus all banks of this cluster belong to the group of risky banks.

**The third cluster** has 1 green indicator, 6 yellow and 5 red indicators. Thus according to the color predominance and red colour rules all banks of this cluster correspond to the group of unsound banks.

The Alliance bank, BTA Bank and SB Home Credit Bank were earlier excluded from the analysis because of abnormal levels of their indicators analysed and distributed into appropriate group. Alliance Bank has 9 red indicators, thus classifying it in the group of financial unsound banks. BTA bank has 5 green indicators, 4 yellow and 3 red indicators which the exceed threshold. This bank should be classified as risky, but its rate of NPL is enormous and hence it is classified as financial unsound. SB Home Credit Bank has 8 green indicators and 4 yellow during the clustering and was classified to the sound group.

### 3.7.2 Interpretation of Structure of Banking Sector by the Degree of Financial Soundness

The obtained bank classified groups according to the degree of financial soundness are analyzed by the median values of financial ratios (Table 3.29). Two groups of banks were obtained on 1st January, 2008 and three groups of banks on 1st January, 2014. This analysis detected changes in the structure of the banking sector according to the degree of financial soundness during the study period. These are the migration of banks between groups and the emergence of a new group of banks.

**Table 3.31: Comparison of the Median Values for Groups of Financial Soundness on 1st January, 2008 and 1st January, 2014**

| Groups of Financial Soundness | | Sound Banks | | Risky Banks | | Financially Unsound Banks | |
|---|---|---|---|---|---|---|---|
| Data | | 01.01. 2008 | 01.01. 2014 | 01.01. 2008 | 01.01. 2014 | | 01.01. 2014 |
| Banks number | | 19 | **9** | 15 | **22** | | **6** |
| Capital to assets ratio | R1 | 0.614 | **0.641** | 0.154 | **0.145** | | **0.150** |
| Regulatory capital to risk-weighted assets | R2 | 0.416 | **0.617** | 0.095 | **0.110** | | **0.107** |
| Regulatory Tier 1 capital to risk-weighted assets | R3 | 0.722 | **0.835** | 0.142 | **0.147** | | **0.124** |
| Equity to debt | R4 | 1.500 | **1.789** | 0.175 | **0.169** | | **0.176** |
| Debt to equity | R5 | 0.667 | **0.559** | 5.719 | **5.943** | | **5.701** |
| NPL to total gross loans | R6 | 0.005 | **0.035** | 0.015 | **0.034** | | **0.413** |
| NPL to capital | R7 | 0.009 | **0.057** | 0.063 | **0.174** | | **3.163** |
| Return on assets | R9 | 0.022 | **0.023** | 0.017 | **0.019** | | **0.003** |
| Earnings before interest and taxes to assets | R11 | 0.050 | **0.023** | 0.053 | **0.063** | | **0.065** |
| Net interest margin | R12 | 0.036 | **0.064** | 0.025 | **0.056** | | **0.041** |
| Interest rate spread | R13 | 0.031 | **0.050** | 0.022 | **0.048** | | **0.008** |
| Current liquidity ratio | R15 | 1.120 | **2.588** | 1.350 | **0.850** | | **1.134** |

*Groups of banks on 1st January, 2014 in bold
**Source:** Author

On 1st January, 2008, two groups have been selected**.** The first group contains the **sound banks** and risky banks are in the second.

**The first group of sound banks** on 1st January, 2008 is characterized by a high level of capital adequacy, the highest net interest rate margin and interest rate spread level among the three groups, a high level of asset quality and a low return on assets.

This group demonstrates a superior combination of parameters such as capital adequacy of R1 at 0.614, R2 at 0.416 and R3 at 0.722 but has a medium return on assets of R9 at 0.022 and of R11 at 0.050, a low rate of NPL of R6 at 0.005 and of R7 at 0.009 and a relatively high level of net interest rate margin of R12 at 0.036 and interest rate spread of R13 at 0.031. These banks have limited or no branch network and their range of banking services in the market is very restricted.

**The second group of risky banks** on 1st January, 2008 show a low level of capital adequacy, a low net interest rate margin and interest rate spread, an adequate quality of assets and medium profitability.

This group is characterized by a capital adequacy that is slightly higher than the normative values of R1 at 0.154, R2 at 0.095 and R3 at 0.142, a low return on assets of R9 at 0.017 and R11 at 0.053, the lowest level of net rate interest margin and interest rate spread of R12 at 0.025 and R13 at 0.022 and an average NPL of R6 at 0.015 and R7 at 0.063.

On 1st January, 2014, three groups were selected. The first contains the **sound banks**, the second are the **risky** banks and the third group are **unsound banks**.

**The first group of sound banks** on 1st January 2014 is characterized by the highest level of capital adequacy, the highest net interest rate margin and interest rate spread level among the three groups, a high level of asset quality and a high level return on assets.

The banks of this group have the highest level of capital adequacy of R1 at 0.641, R2 at 0.617 and R3 at 0.835 pointing to their conservative financial policy, high level of net interest rate margin and interest rate spread of R12 at 0.064 and R13 at 0.050 and an acceptable level of NPL to loans and NPL to capital of R6 at 0.035 and R7 at 0.057. The return to assets is high among the three groups with R9 at 0.023.

**The second group of risky banks** on 1st January, 2014 shows a low level of capital adequacy, an average net interest rate margin and interest rate spread, an average quality of assets and high EBIT to assets in comparison with the other two groups.

This group has the features of low capital adequacy of R1 at 0.145, R2 at 0.110 and R3 at 0.147, a medium interest rate margin R12 at 0.056 and net interest rate spread of R13 at 0.048 and an acceptable level of NPL to total gross loans of R6 at 0.034, and high NPL to capital at 0.174. The R9 return on assets for this group is average at 0.019.

**The third group of unsound banks** on 1st January, 2014 shows a low level of capital adequacy, a low net interest rate margin and interest rate spread, the lowest quality of assets and return on assets and the highest debt to equity ratio.

This group has capital adequacy of R1 at 0.150, R2 at 0.107 and R3 at 0.124, low interest rate margin and net interest rate spread of R12 at 0.041 and of R13 at 0.008, the highest NPL of R6 at 0.413 and R7 at 3.163 and the lowest return on assets of R9 at 0.003.

There has been a marked deterioration in the quality of assets on 1st January, 2014. In all the groups, the NPL to total gross loans and capital has increased significantly for all the selected clusters.

On 1st January, 2014 a new group of financially unsound banks appeared. Below is shown the structure of the banking sector by the number of banks and by their share in banking sector assets on 1st January, 2008 and 1st January, 2014 (Table 3.32).

**The first group of sound banks** had 19 members on 1st January, 2008 and 9 on 1st January, 2014. Only the 7 banks of SB Taib Kazakh Bank, SB NB of Pakistan in Kazakhstan, Zaman-Bank, Dana bank (renamed SB PNB Kazakhstan), SB KZI bank, Demir Kazakhstan Bank (renamed Bank Positive Kazakhstan) and MB Alma-Ata (renamed Home Credit Bank) were able to remain in this group since 2008. The rest have moved to the group of risky banks.

**The second group of risky banks** had 15 members on 1st January, 2008 and 22 banks on 1st January, 2014. 6 banks from this group in 2008 became unsound in 2014 and 9 remained in this category.

On 1st January, 2014 the **third group of financially unsound banks** appeared. The group consists of Kazkommertsbank, BTA Bank, ATF Bank, Alliance Bank, Temirbank and Nurbank.

**Table 3.32: Comparison of the Clusters on 1st January, 2008 and 1st January, 2014**

| 2008 | | | | | 2014 | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Group | № | Bank | Assets, thousand tenge` | Cumulative Share, % | Group | № | Bank | Assets, thousand tenge | Cumulative Share, % |
| Sound banks | 1 | Metrokombank (ForteBank)** | 2 834 457 | 0.02 | Sound banks | 1 | Bank Positive Kazakhstan | 21 374 823 | 0.14 |
| | 2 | Express Bank (dissolved) | 2 343 627 | 0.04 | | 2 | SB PNB Kazakhstan | 13 815 151 | 0.23 |
| | 3 | SB Taib Kazakh Bank | 2 031 368 | 0.06 | | 3 | SB KZI Bank" | 26 103 968 | 0.40 |
| | 4 | SB Bank of China in Kazakhstan | 7 250 308 | 0.12 | | 4 | Zaman Bank | 14 559 171 | 0.50 |
| | 5 | SB NB of Pakistan in Kazakhstan | 1 385 489 | 0.13 | | 5 | Islamic Bank Al Hilal (new) | 17 042 020 | 0.61 |
| | 6 | Zaman-Bank | 1 585 040 | 0.15 | | 6 | Shinhan Bank Kazakhstan (new) | 17 481 962 | 0.73 |
| | 7 | Kazinkombank (Bank RBK)** | 1 727 675 | 0.16 | | 7 | SB Taib Kazakh Bank | 21 296 912 | 0.87 |
| | 8 | SB Lariba-Bank (AsiaCredit Bank)** | 6 403 704 | 0.21 | | 8 | SB NB of Pakistan in Kazakhstan | 5 559 666 | 0.91 |
| | 9 | Senim-Bank (Qazaq Banki)** | 2 500 083 | 0.24 | | 9 | Home Credit Bank | 117 411 622 | 1.68 |
| | 10 | SB Sberbank of Russia | 61 696 674 | 0.77 | Risky Banks | 1 | AsiaCredit Bank | 92 261 521 | 2.29 |
| | 11 | Masterbank (dissolved) | 2 020 556 | 0.78 | | 2 | Bank RBK | 222 774 461 | 3.77 |
| | 12 | Delta Bank | 19 991 232 | 0.95 | | 3 | Delta Bank | 190 265 795 | 5.03 |
| | 13 | Danabank (SB PNB Kazakhstan)** | 6 204 988 | 1.01 | | 4 | ForteBank | 38 309 287 | 5.28 |
| | 14 | SB Alfa-Bank | 25 364 818 | 1.22 | | 5 | Kaspi Bank | 850 885 474 | 10.92 |
| | 15 | SB KZI bank | 9 009 977 | 1.30 | | 6 | Qazaq Banki | 48 646 723 | 11.24 |
| | 16 | Demir Kazakhstan Bank (Bank Positive Kazakhstan) ** | 14 652 436 | 1.43 | | 7 | Bank Astana-Finance (new) | 79 551 726 | 11.76 |
| | 17 | MB Alma-Ata (Home Credit Bank) ** | 4 109 331 | 1.46 | | 8 | Bank Kassa Nova | 56 213 609 | 12.14 |
| | 18 | Eximbank Kazakhstan | 38 566 758 | 1.79 | | 9 | Bank CenterCredit | 1 072 420 146 | 19.23 |
| | 19 | TPBK | 5 569 591 | 1.84 | | 10 | SB Alpha Bank | 171 023 614 | 20.37 |
| Risky Banks | 1 | Alliance Bank | 1 192 069 512 | 12.06 | | 11 | Eurasian Bank" | 587 432 104 | 24.26 |
| | 2 | ATF Bank | 989 598 391 | 20.55 | | 12 | Kazinvestbank | 92 845 730 | 24.87 |
| | 3 | Bank Caspian (Kaspi Bank) ** | 257 422 487 | 22.76 | | 13 | Halyk Bank of Kazakhstan | 2 441 764 274 | 41.03 |
| | 4 | Bank Turanalem (BTA bank) ** | 2 648 603 166 | 45.47 | | 14 | Citibank Kazakhstan | 324 764 700 | 43.18 |
| | 5 | Bank CenterCredit | 880 897 912 | 53.02 | | 15 | TPBK | 49 466 476 | 43.51 |
| | 6 | SB ABN Amro Bank (SB RBS Kazakhstan) ** | 120 568 110 | 54.06 | | 16 | Tsesnabank | 923 678 751 | 49.63 |
| | 7 | Eurasian Bank | 183 796 839 | 55.63 | | 17 | Eximbank Kazakhstan | 55 096 555 | 49.99 |

**Source:** Author

Continuation of table 3.32

| 2008 | | | | | 2014 | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Group** | **№** | **Bank** | **Assets, thousand tenge`** | **Cumulative Share, %** | **Group** | **№** | **Bank** | **Assets, thousand tenge** | **Cumulative Share, %** |
| | 8 | Kazinvestbank | 57 936 011 | 56.13 | | 18 | SB RBS (Kazakhstan) | 51 948 481 | 50.33 |
| | 9 | Kazkommertsbank | 2 714 259 363 | 79.40 | | 19 | SB Bank of China | 104 705 262 | 51.03 |
| | 10 | Halyk Bank of Kazakhstan | 1 567 245 252 | 92.84 | | 20 | SB HSBC Bank Kazakhstan | 187 463 153 | 52.27 |
| | 11 | Nurbank | 204 040 360 | 94.59 | | 21 | SB Sberbank | 1 035 822 483 | 59.12 |
| | 12 | Citibank Kazakhstan | 81 856 079 | 95.29 | | 22 | VTB Bank Kazakhstan (new) | 143 964 144 | 60.08 |
| | 13 | Tsesnabank | 150 039 231 | 96.58 | Unsound banks | 1 | Kazkommertsbank | 2 500 987 142 | 76.63 |
| | 14 | SB HSBC Bank of Kazakhstan | 72 496 077 | 97.20 | | 2 | Nurbank | 252 801 791 | 78.31 |
| | 15 | DO Temirbank | 325 928 185 | 100.00 | | 3 | ATF Bank | 895 248 252 | 84.23 |
| | | | | | | 4 | Temirbank | 302 608 237 | 86.24 |
| | | | | | | 5 | BTA Bank | 1 516 956 022 | 96.28 |
| | | | | | | 6 | Alliance Bank | 562 026 334 | 100.00 |

** Renamed

**Source:** Author

In order to understand the true extent of the deterioration of the financial situation of the banking sector of Kazakhstan, these groups were analysed from the perspective of the size of bank assets to estimate the proportion of each group in the total assets of the banking sector (Table 3.33).

**Table 3.33: Share of Groups in Banking Sector Total Assets**

| Groups of Banks | 1st January, 2008 | | | 1st January, 2014 | | |
|---|---|---|---|---|---|---|
| | Number of banks | Share, % | Share in banking sector assets, % | Number of banks | Share, % | Share in banking sector assets, % |
| Sound Banks | 19 | 56 | 1.84 | 9 | 24 | 1.68 |
| Risky Banks | 15 | 44 | 98.15 | 22 | 60 | 58.39 |
| Unsound | 0 | 0 | 0 | 6 | 16 | 39.92 |
| **Total** | **34** | **100** | **100.00** | **37** | **100** | **100.00** |

**Source:** Author

Share of groups in banking sector total assets **on** 1st **January, 2008:**

**The first group of sound banks** has 19 members or approximately 56**%** of the total number of banks**.** Their assets are 1.84% of the banking sector.
**The second group of risky banks** has 15 members or 44% of the total number of banks. They have 98.15% of the banking sector's total assets.

Share of groups in banking sector total assets **on** 1st **January, 2014:**

**The first group** is the sound banks**.** There are 9 banks or approximately 24% of the total. Assets of this cluster amount to 1.68% of the total of the banking sector.
**The second group** consists of risky banks. There are 22 banks or approximately 60% of the total. Their assets are 58.39% of the banking sector's total assets;
**The third group** consists of unsound banks. There are 6 banks or 16% of the total. Their assets are 39.92% of the banking sector's total assets. Two of the six financially unsound banks are among the five largest banks in Kazakhstan. Kazkommertsbank is the largest bank in terms of assets on 1st January, 2014.

6 financial unsound banks are BTA Bank, Kazkommertsbank, ATF Bank, Alliance Bank, Temirbank and Nurbank. Government acquired 75% of BTA bank stake, 20% of Kazkommertsbank and Alliance bank was sold by owners for $1 to government. ATF Bank, Temirbank and Nurbank were unable to meet their scheduled payments. In 2015 BTA Bank merged with Kazkommertsbank; Alliance Bank and Temirbank merged with Forte bank. Thus, the unsoundness of 6 banks obtained by cluster analysis on the 1st of January, 2014 was proved completely.

Comparing the results of banks clustering in 2008 with the results of ranking for the same period obtained in section 3.6.1, we can note the following: all 19 sound banks are in the first 21 banks in ranking. Thus, the results of Cluster Based Methodology almost completely coincide with the results of ranking. Exceptions are: the Alliance Bank and Kazinvestbank. In this case, cluster analysis caught the deteriorating trend in financial performance of Alliance Bank which defaulted in April 2009.

The results of the comparison of the ranking with the cluster analysis in 2014 are the following: 9 banks identified by cluster analyses as sound are the first 9 banks in ranking. From 6 unsound banks 5 are in the last places in ranking (33-37). Only unsound bank Kazkommertsbank was ranked as 23rd in ranking. In this case, same in 2008, Cluster Based Methodology more reliably captured the tendency of the deteriorating financial statement of Kazkommertsbank. It received financial assistance from government in 2016 and it was sold to Halyk Bank for $ 1 in 2017.

### 3.7.3 Comparison of the Results of Ranking and Cluster Based Methodology

Comparison of the results of ranking and Cluster Based Methodology for two years are presented in Table 3.34 . As could be seen from the table, the results of Cluster Based Methodology almost completely coincide with the results of ranking. Exceptions are: the Alliance Bank and Kazinvestbank. In this case, cluster analysis caught the deteriorating trend in financial performance of Alliance Bank which defaulted in April 2009.

**Table 3.34: Comparative Table of Ranking Scores of Banks with Results of Cluster Based Methodology**

| 2008 | | | 2014 | | |
|---|---|---|---|---|---|
| **Banks** | **Total Score** | **Average Score** | **Banks** | **Total Score** | **Average Score** |
| **1** | **2** | **3** | **4** | **5** | **6** |
| Masterbank | 89 | 7,42 | SB PNB Kazakhstan | 93 | 7,75 |
| SB Bank of China in Kazakhstan | 79 | 6,58 | SB NB of Pakistan in Kazakhstan | 91 | 7,58 |
| Senim-Bank | 76 | 6,33 | Zaman Bank | 85 | 7,08 |
| SB Lariba-Bank | 76 | 6,33 | SB KZI Bank | 79 | 6,58 |
| Zaman-Bank | 74 | 6,17 | Islamic Bank Al Hilal | 79 | 6,58 |
| TPBK | 74 | 6,17 | Shinhan Bank Kazakhstan | 79 | 6,58 |
| Express Bank | 69 | 5,75 | Home Credit Bank | 74 | 6,17 |
| SB NB of Pakistan in Kazakhstan | 66 | 5,50 | Bank Positive Kazakhstan | 67 | 5,58 |
| SB Alfa-Bank | 66 | 5,50 | SB Taib Kazakh Bank | 67 | 5,58 |
| SB Taib Kazakh Bank | 64 | 5,33 | SB RBS | 58 | 4,83 |
| Kazinkombank | 63 | 5,25 | Bank Kassa Nova | 58 | 4,83 |

**Source:** Author

Continuation of Table 3.34

| 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| SB Sberbank of Russia | 63 | 5,25 | Eximbank Kazakhstan | 57 | 4,75 |
| Delta Bank | 62 | 5,17 | ForteBank | 56 | 4,67 |
| Eximbank Kazakhstan | 62 | 5,17 | AsiaCredit Bank | 56 | 4,67 |
| Metrokombank | 60 | 5,00 | Kaspi Bank | 53 | 4,42 |
| MB Alma-Ata | 59 | 4,92 | Delta Bank | 52 | 4,33 |
| Alliance Bank | 58 | 4,83 | TPBK | 50 | 4,17 |
| Kazinvestbank | 58 | 4,83 | Bank Astana-Finance | 50 | 4,17 |
| SB KZI bank | 56 | 4,67 | SB Alpha Bank | 50 | 4,17 |
| Demir Kazakhstan Bank | 56 | 4,67 | SB Bank of China | 50 | 4,17 |
| Danabank | 55 | 4,58 | Eurasian Bank" | 50 | 4,17 |
| Bank Turanalem | 54 | 4,50 | SB Sberbank | 50 | 4,17 |
| Nurbank | 53 | 4,42 | Kazkommertsbank | 49 | 4,08 |
| DO Temirbank | 53 | 4,42 | Halyk Bank of Kazakhstan | 48 | 4,00 |
| SB ABN Amro Bank | 51 | 4,25 | Citibank Kazakhstan | 48 | 4,00 |
| Bank CenterCredit | 50 | 4,17 | SB HSBC Bank Kazakhstan | 47 | 3,92 |
| Eurasian Bank | 50 | 4,17 | VTB Bank Kazakhstan | 47 | 3,92 |
| Citibank Kazakhstan | 49 | 4,08 | Qazaq Banki | 47 | 3,92 |
| Tsesnabank | 49 | 4,08 | Bank RBK | 46 | 3,83 |
| SB HSBC Bank of Kazakhstan | 48 | 4,00 | Tsesnabank | 46 | 3,83 |
| ATF Bank | 46 | 3,83 | Bank CenterCredit | 45 | 3,75 |
| Halyk Bank of Kazakhstan | 46 | 3,83 | Kazinvestbank | 45 | 3,75 |
| Bank Caspian | 45 | 3,75 | Temirbank | 42 | 3,50 |
| Kazkommertsbank | 44 | 3,67 | BTA Bank | 39 | 3,25 |
| | | | ATF Bank | 37 | 3,08 |
| | | | Nurbank | 36 | 3,00 |
| | | | Alliance Bank | 30 | 2,50 |

**Source:** Author

The results of the comparison of the ranking with the cluster analysis in 2014 are similar to the classifications from the universial ranking system: 9 banks identified by cluster analyses as sound are the first 9 banks in ranking. From 6 unsound banks 5 are in the last places in ranking (33-37). Only unsound bank Kazkommertsbank was ranked as 23rd in ranking. In this case, same in 2008, Cluster Based Methodology more reliably captured the tendency of the deteriorating financial statement of Kazkommertsbank. It received financial assistance from government in 2016 and it was sold to Halyk Bank for $ 1 in 2017.

### 3.8 Summary

In this study the main focus is to assess the financial soundness of the Kazakhstan banking sector using cluster analysis to group banks by the extent of financial soundness by classification of unsound, risky and sound. After the fundamentals of banking financial soundness was presented and the relevant literature was discussed and evaluated, descriptive, PCA and cluster analysis procedures were carried out on a relevant sample to show empirical results.

The cluster based methodology allowed the researcher to assess financial soundness and identify the structure of the banking sector of Kazakhstan, on 1st January, 2008 as: **I group – sound banks, II group – risky banks.**

On 1st January, 2014 they were identifiedas: **I group – sound banks, II group – risky banks, III group – unsound banks.** Thus, in 2014 a new Group III of financial unsound banks appeared.

The empirical results of this chapter indicate that cluster analysis is able to identify the structure of the banking sector by the extent of its financial soundness using selected indicators. Selected financial ratios are the warning indicator, reflecting capital adequacy, profitability, asset quality and liquidity. This proposed cluster based methodology of the Kazakh banking sector's financial soundness identifies the degree of bank financial soundness by unsound, risky and sound categories, and it is argued that this methodology may help to prevent bank failures. It is recommended that cluster analysis should be tested and employed to improve bank monitoring and supervision.

It is necessary to note the dramatic deterioration of the structure of the banking sector according to the extent of financial soundness. On 1st January, 2008 there were no unsound banks in Kazakhstan. Risky banks were 47% of the total, and sound banks were 53%. On 1st January, 2014, unsound banks were 16%, risky banks were 60% and sound banks were 24%.

The depth of the financial fragility of Kazakhstan banks is even more clearly manifested in that two of the six financial unsound banks are in the top five largest banks of Kazakhstan. The assets of financial unsound banks account for 39% of the entire banking system of Kazakhstan.

Additionally, the cluster based methodology of assessment of banking sector financial soundness determined six unsound and thirty one sound banks on 1st January, 2014. The status of 'sound' and 'unsound' will be used to construct financial unsoundness prediction models in the next chapters.

# CHAPTER 4 THE APPLICATION OF ALTMAN MODELS ON KAZAKHSTAN BANKS


## ABSTRACT

**Purpose –** Due to the risky nature of a banking system, it is essential to have a model that can accurately identify the financial unsoundness of banks. This study tests the ability of the Altman model to detect and predict the financial unsoundness of Kazakhstan banks.

**Design and Methodology Approach –** The Z (1993) – the Four-Factor Altman Model for non-manufacturing companies and EM Score (1995) – the Four-Factor Altman Model for emerging markets are tested on Kazakhstan banks in order to assess their ability to predict financial unsoundness. Annual data from 12 Kazakhstan banks across the period of 1st January 2008 to the 1st January 2014 were selected. The sample consists of 6 sound and 6 unsound banks. Unsound banks were identified by Cluster Analysis in Chapter 3. Sound banks were isolated from the group of financially sound banks in terms of asset size, specialization and branch network. Then original models are re-estimated to improve their predictive accuracy. Cutoff points in the original and re-estimated models were changed according to the technique that was used in Begley et al. (1996) and Wu et al. (2010).

**Findings –** The results indicate that the original Z (1993) model for non-manufacturing companies and the EM Score (1995) model for emerging markets have low predictability at 45.2% and 44.1% respectively. Slight performance improvements were found in the re-estimated models. Re-estimating Z-score using Direct and Wilks' methods improved the accuracy of the prediction to 63.1% and 61.9%, respectively. The cutoff point was changed by a percentile, which improved the predictive accuracy for both models and reduced the sum of Type I and Type II errors. However, the predictive accuracy of the original and re-estimated models is weaker than Altman's results in the 1990s.

**Practical Implications –** Altman models are widely used by academicians and practitioners around the world. This study demonstrates that tested and re-estimated Altman models have a modest ability to predict financial unsoundness in Kazakhstan. Also, the new cutoff points have slightly improved the overall predictability and significantly reduced the Type I errors.

**Originality/Value –** This study is the first to test the Altman Z (1993) and EM Score (1995) models on Kazakhstan banks and assess their ability to predict changes in their financial soundness status.

**Importance:** This chapter is a starting point of the search for a superior unsoundness prediction model for banks. It is the first attempt to apply the original and re-estimated Z (1993) and EM score (1995) models for the sample of Kazakhstan banks.

## 4.1 Introduction

The prediction of financial unsoundness started with Altman's foremost model. In 1968, the Z-Score model developed by Altman was the first to predict company failure based on financial data. Ever since then academicians and practitioners around the world have employed or modified the original Altman models, mostly for the US and other developed countries. Considerably fewer studies are conducted for emerging countries (Allayannis et al., 2003, Merkevicius et al., 2006, Othman, 2013, Rankov and Kotlica and 2013 Pradhan, 2014). This study contributes to the literature by employing and modifying Altman's Z-score models to predict the financial unsoundness of Kazakhstan banks.

The purpose of this chapter is to evaluate the ability of Altman's models to predict the financial unsoundness of Kazakhstan banks. The models have a number of indisputable advantages such as simplicity, the possibility of use with limited information, comparability of indicators, the possibility of splitting the analysed companies into potentially bankrupt and non-bankrupt firms and high accuracy of calculations. However, some researchers believe that these models cannot be used in modern conditions outside the United States and suggested the use of re-estimated coefficients of the models to improve their predictive accuracy (Moyer, 1977; Grice and Ingram, 2001, Popov and Kadyrov, 2014). Furthermore, Grice and Ingram (2001) found that the Altman models are useful for predicting financial stress conditions in addition to bankruptcy.

Using data from Kazakhstan banks, this chapter estimated the efficiency of Altman's classical models of **the Four-Factor Altman Z (1993) Model** and **the Four-Factor Altman EM Score (1995) Model**. In line with Moyer (1977), Merkevicius et al. (2006), Wu et al. (2010) and Ho et al. (2013), both models were re-estimated to improve their predictive accuracy. The direct approach compulsorily includes all four variables specified by Altman in the discriminant function. The Wilks' approach enters variables into the function in a stepwise manner up to the point where the Wilks' lambda is minimized. Cutoff points were changed to increase the predictive accuracy.

## 4.2 Literature Review

The majority of bankruptcy prediction studies noted that Altman models are simple, comparable and frequently used because they demonstrate high predictability (Griffin and Lemmon, 2002, Allayannis et al., 2003, Hillegeist et al., 2004, Xu and Zhang, 2009, Othman, 2013, Chieng, 2013, Rankov and Kotlica, 2013 and Popov and Kadyrov, 2014). The Altman Z-score model was cited 12,376 times according to Google Scholar on 28/11/2016. The purpose of this section is to review the models and then to select the most applicable version to predict the financial unsoundness of Kazakhstan banks. This section first considers the concept of financial unsoundness and its links with such concepts as bankruptcy, failure, distress and others. It then continues with the review of the original and re-estimated Altman models.

### 4.2.1 Bank Financial Unsoundness

As mentioned in Chapter 3 this study followed Puhov's (2013) definition of financial soundness as a quantitative and qualitative condition of equity, assets and liabilities which provides a strengthening of reliability and stability of bank activity, assuring increased confidence. It is broader than the concept of solvency to which the idea of soundness is often equated. In its turn, the concept of reliability is narrower and refers to a bank's ability to withstand all the negative factors of the market.

Concepts of financial soundness and unsoundness are widely used in IMF publications (Čihák and Schaeck, 2007, Babihuga, 2007 and Navajas and Thegeya, 2013). It is necessary to note that all IMF papers focus on the cross-country level and predict the financial unsoundness of the banking sector and the financial system of a number of countries. There are many studies devoted to the prediction of bank bankruptcy, bank failure, bank distress and bank default while only a few studies forecast bank financial unsoundness such as those by Gaganis et al. (2006), Ioannidis et al. (2010), Ginevicius and Podviezko (2013), Bourkhis and Nabi (2013) and Camelia and Angela (2013) (details in Section 3.2.2). Indeed, related terms usually used in the literature are distress, default, failure,  and bankruptcy (Othman, 2013). Various authors use different definitions and meanings attached to the concepts in their research (Table 4.1).

**Table 4.1: Definitions of Terms Related to Financial Unsoundness**

| Source | Definition |
|---|---|
| 1 | 2 |
| Beaver (1966) | Failure is defined as the inability of a firm to pay its financial obligations as they mature. Operationally, a firm is said to have failed when any of the events of bankruptcy, bond default, nonrepayment of a loan due or nonpayment of a preferred stock dividend have occurred. |
| Sinkey (1975) | A Problem Bank is one which in the opinion of the US federal banking agencies has violated the law or control requirements or was engaged in "unsafe or unsound" banking practice that endangered the current or future solvency of the bank. |
| Golovan et al. (2003) | Bankruptcy is a legal situation when the license has not been revoked but the bank has been taken under the control of a government authority such as the Agency for Restructuring of Russian Federation. |

**Source:** Author

Continuation of Table 4.1

| 1 | 2 |
|---|---|
| Abudu and Markose (2007) | Bank Failure according to the criteria of the USA results in the closure of financial institutions and banks. The US Federal Deposit Insurance Corporation (FDIC) consider that banks fail when they have been rendered assistance by government, they have been acquired by offers of a partial purchase from government or they have had problems with payment of liabilities |
| Arena (2008) | A bank will be considered to have failed if it fits into any of the following categories: (1) Either the central bank or a government agency, specifically created to address the crisis, recapitalized the financial institution or the institution required a liquidity injection from the monetary authority. (2) The government temporarily suspended (‘‘froze’’) the financial institution’s operations. (3) The government closed the financial institution. |
| Othman (2013) | A bank is defined as bankrupt if it experiences to liquidation, takeover or merger,  or its capital adequacy ratio falls below 8 percent all due to illiquidity or insolvency |
| Rankov and Kotlica (2013) | Financial Distress begins when an organization is unable to meet its scheduled payments or when the projection of future cash flows points to an inability to do so in the near future |
| Mousavi, Ouenniche and Xu (2015) | Bankruptcy of a company happens when it is experiencing losses and becomes insolvent when realisable asset values are less than liability values |

**Source:** Author

All definitions mentioned above are connected with the obvious signs of bankruptcy such as license revocation, liquidation, restructuring, and takeover or merger. In current research the definition of unsoundness is connected with changes in financial ratios that show a deterioration in a bank financial state. A bank becomes unsound when there is deterioration in its capital adequacy, asset quality and profitability. Thus, supplementing Puhov’s (2013) definition, financial unsoundness is a condition of a bank in which the indicators characterizing capital adequacy, asset quality and liquidity, as well as its effectiveness, fell below certain limits. A group of unsound banks was identified using these limits of financial soundness in Chapter 3.

Chapter 2 clearly demonstrates that the main financial indicators show stagnation in Kazakhstan's banking sector. Bank loan portfolio as a share of GDP decreased from 69% in 2008 to 38% in 2014 and, over the same period, the ratio of bank customer deposits to GDP decreased from 50% to 28%, non-performing loans to total lending across the sector had increased to 36% compared to 2.7% in 2008 and the national currency of the tenge depreciated by almost 200% (nationalbank.kz). International rating agencies downgraded the debt ratings of Kazakh banks (Table 2.1). For the analysed period none of the Kazakhstan banks have credit ratings higher than BBB. Thus the general standards could not be applied to Kazakh banks. Therefore, supervision and monitoring bodies need a unique system/model to assess bank financial soundness and detect early signs of financial unsoundness in Kazakhstan banks.

Researchers consider terms like such as “unsound”, “problem”, “distressed” and “failed” as the steps which lead to bankruptcy. Bankruptcy is the worst case scenario for an organization and therefore the majority of research studies examine this case. “Insolvency”, “failure” and “default” are other terms which have different definitions. Altman believes that all can be combined in the concept of “distress” and have certain common features and signs of potential distress that appears long before bankruptcy (Altman, 1993). This study regards financial unsoundness as an earlier step towards distress, reflecting vulnerable and unsafe conditions in the Kazakhstan’s banking sector.

Many researchers use Altman models as a measure of distress, in addition to bankruptcy, i.e. Grice J.S., Ingram R.W. (2001), Franzen L.A. et al. (2007), Pindado J. et al. (2008), Chen H. et al. (2012), Singhal R., Zhu Y. (2013) and Othman (2013). It is confirmed that Altman models have a high predictive accuracy to detect and predict distress. This chapter tests the efficiency of Altman’s model of the prediction of bank financial unsoundness.

### 4.2.2 Review of Altman Models

Altman was one of the pioneers who used financial ratios as predictors of bankruptcy. Beaver (1966), Deakin (1972) defined financial ratios that measure profitability, liquidity and solvency as the most significant indicators. Altman (1968) states that the selection of financial ratios must meet requirements that (1) ratios are the most important in detecting bankruptcy potential, (2) weights should be attached to those selected ratios, and (3) the weights should be objectively established.

Altman (1968) chose multiple discriminant analysis (MDA) as the appropriate statistical technique and noted that the advantage of dealing with classification problems was the potential to analyze the entire variable profile of the object simultaneously rather than sequentially examining its individual characteristics.

Altman Z score model (1968) was the pioneering work on failure prediction models and later it became the basis for the other well-known ZETA, Z’, Z” and EM Score models by Altman. These models were modified in terms of economic development, country and industry features.

Altman et al. (2014) explored academic papers published in prominent international journals since 2000 and selected 34 articles where the Z Score or Z Score methodology were used. Frequent usage of the Z-Score Model as a measure of financial distress indicated that it is widely accepted as a reputable, simple and reliable measure of distress. Altman found that among the 34 studies, in 17 cases Altman's Z-Score Model was used as the measure of distress, in 14 studies Altman's original model was verified and/or modified and in 3 cases it was used for a robustness check. Also, many authors used the Altman Z-Score Model for different economic and financial research purposes as a venerable and simple prediction model (Table 4.2).

**Table 4.2: Prior Studies and Use of Altman Models**

| Study | Sample | Industry | Country | Results |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| Moyer, 1977 | paired sample of 27 bankrupt and 27 nonbankrupt firms during 1965-1975 | Firms | USA | Tested and Re-estimated Altman's (1968) five factor Z score model and obtained high predictive accuracy |
| Coats and Fant, 1993 | 47 distressed firms and 94 viable firms | Firms | USA | Used a set of five variables from Altman's model (1968). Based on this variables built four MDA models. These models served as benchmarks to compare with neural network approach. |
| Begley et al., 1996 | 100 non-bankrupt firms, matched with 100 bankrupt firms on the basis of COMPUSTAT 1980-1989 | Firms | USA | Re-estimated Altman's (1968) Z score and Ohlson's models and made a conclusion that these models prediction accuracy decreased in more recent periods. Both original and re-estimated models reached 78% prediction accuracy. |
| Grice and Ingram, 2001 | 148 distressed and 824 non-distressed firms1985–1987 - training sample for re-estimation and 148 distressed and 854 non-distressed firms 1988– 1991 prediction sample | Firms | USA | The Type I (Type II) errors for the Altman (1968) model were lower (higher) than those for the re-estimated models. Other results of this study indicate that those who employ Altman's Z-score model should re-estimate the model's coefficients rather than rely on those reported by Altman (1968). |
| Griffin and Lemmon, 2002 | NYSE, Nasdaq, Amex reports from July 1965 to June 1996 | Firms | USA | Used Z score model as robustness check investigating the relationship between book-to-market equity, distress risk and stock returns. They found that the difference in return between high and low book-to-market equity securities in a group of firms with the highest risk of distress was more than twice higher than in other cases. |

**Source:** Author

Continuation of Table 4.2

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Allayannis et al., 2003 | 327 companies from 1996-1998. | Non-Financial Companies | East Asia | Used modified Altman (2000) Z-score as one of the financial performance measures |
| Chava and Jarrow , 2004 | 1962-1999 period with 1461 bankruptcies | publicly listed companies | USA | Compared Altman (1968), Zmijewski and Shumway models with the market-based model. Market-based model outperformed others. Altman model correctly identified 63.2% of bankruptcies. |
| Hillegeist et al., 2004 | 78,100 firm-years for solvent and bankrupt firms from 1980 and 2000, | Firms | USA | Assessed Altman (1968) Z score and Ohlson (1980) models and compared them with developments based on the Black–Scholes–Merton option-pricing model. BSM-Prob. BSM-Prob provides significantly more information about the probability of bankruptcy than Z score or O score |
| Merkevicius et al., 2006 | “traindata” with 1108 records and “testdata” with 742 records for 2004. | Firms | Lithuania | The hybrid model was developed with the use of Altman’s z-score model with the changed weights for variables and self-organizing map. Hybrid SOM-Altman’s model reached the prediction rate of 92.35%. |
| Clarke J. et al., 2006 | 289 bankrupt and 289 non-bankrupt firms | Firms | USA | Altman’s Z-score was calculated two years preceding the bankruptcy year. |
| Reisz and Perlich, 2007 | 33,238 non-bankrupt and 799 bankrupt industrial firms from 1988 to 2002 | Industrial Firms | USA | Used barrier option model for bankruptcy prediction and compared its discriminatory power with Altman’s market-based and accounting-based Z-score and Z”-score models. They proved the superiority of Altman’s z-score and Z”-score for short-term bankruptcy prediction. |
| Agarwal and Taffler, 2008 | 15,384 firm-years between 1985-2001 of failure, non-failure firms | Non-Finance Firms | UK | Compared the performance of two alternative formulations of market-based models for the prediction of corporate bankruptcy with a well-established accounting- based models that were represented by Taffler’s (1984) UK Z-score, based on Altman (1968). |
| Sueyoshi and Goto, 2009 | 951 samples as non-default firms and 50 samples as default firms over 1991–2004 | Firms | USA | Compared DEA with DEA–DA from the perspective of bankruptcy assessment. Linkage to Altman’s Z score was one of 10 criteria. |

**Source:** Author

Continuation of Table 4.2

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Xu and Zhang, 2009 | 3,510 listed companies from 1992 to 2005 as bankrupt, non-bankrupt | Listed Companies except Financial Institutions | Japan | Found that the traditional measures, such as Altman's (1968) Z-score, Ohlson's (1980) O-score and the option pricing theory-based distance-to-default, previously developed for the U.S. market, are also individually useful for the Japanese market. Moreover, the predictive power is substantially enhanced when these measures are combined. |
| Wu et al., 2010 | 887 bankruptcies and 49,724 non-bankrupt firms from 1980 to 2006 | Firms | USA | Tested and Re-estimated Altman's five factor Z score model. Found that the MDA model of Altman (1968) performs poorly relative to other five compared models. |
| Vaziri et al., 2012 | 100 banks are selected as samples of which 3 are acquired banks, 17 are helped by the government after the crisis, 20 have claimed bankruptcy and 60 are active from 2001 to 2010 | Banks | USA | Tested Moody's financial ratios, Standard and Poor's financial ratios, Vaziri's financial ratio, Altman's Z-score and then applied logit model and discriminant analysis. Of all the models Z-score model gives the best prediction. Its prediction percentage of failed banks is 80% and shows 75% correct prediction before two years. |
| Othman, 2013 | 13 Islamic and 10 conventional to test Altman's model | Banks | Malaysia | Compared Islamic and conventional bank performance using Altman's models of Z" and EM score. |
| Chieng, 2013 | 4 distressed and 4 control banks over 2007-2012 period | Banks | Eurozone | Found the Z" Score model is a reliable predictor of Eurozone bank failure within five years prior to bankruptcy. |
| Ho et al., 2013 | 122 individual firms, 12 of which filed for bankruptcy over 1990 to 2009 | Firms | USA | Z score Altman (1968) original model does not carry over to their sample. The re-estimated model showed high productive ability. |
| Rankov and Kotlica, 2013 | 10 banks, 5 operated with losses and 5 with profit | Banks | Serbia | Tested the predictability of the Altman and Beaver models. They recommend the use of models for forecasting the probability of bank failure as an early warning system to prevent the bankruptcy of commercial banks in Serbia. |

**Source:** Author

Continuation of Table 4.2

| 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|
| Pradhan, 2014 | 3 banks 2000-2008 | Banks | India | Provided the Z score value for the public sector banks. The Z-score internal parameter estimates were considered from 2001 to 2007 and were applied to train the back propagation neural network and subsequently estimates of the year 2008 to 2013. The data values were used for validation. |
| Hogan, 2014 | 3887 observations, from 1999-2010 | Banks | USA | Used banks' Z-score as the dependent variable. |
| Castagnolo and Ferro, 2014 | 328 actual defaults, bankruptcies or liquidations from 10,439 firms | Firm | USA | Examined four existing models of O-score, Z-score, Campbell, and Merton distance to default model (MDDM). The Z-score model does not have the statistical power to predict defaults. |

**Source:** Author

It can be seen from Table 4.2 that the review of previous studies highlighted the following issues:

Firstly, Altman's models were employed mainly for studies in developed countries. A vast majority of the research studies were conducted in the USA (Griffin and Lemmon, 2002, Wu et al., 2010, Ho et al., 2013 and Hogan, 2014) and also UK (Agarwal and Taffler, 2008), Japan (Xu and Zhang, 2009), Eurozone (Chieng, 2013). According to Altman (2014), classification of developing and developed countries deviated from the traditional grouping. In the context of failure prediction, a developed country has the main characteristics of a long history of failure prediction studies; availability of corporate financial data; the existence of bankruptcy laws and banking infrastructures simplify failure identification; limited government intervention and investors' protection. However, in developing counties, the above factors are absent and company failure is harder to identify due to government protection. Altman models were employed to predict failure in the following developing countries: of East Asian countries (Allayannis et al., 2003), Lithuania (Merkevicius et al., 2006), Malaysia (Othman, 2013), Serbia (Rankov and Kotlica, 2013) and India (Pradhan, 2014).

Secondly, Altman's models were used to predict not only bankruptcy but also distress (Coats and Fant, 1993, Grice and Ingram, 2001 and Chieng, 2013), failure (Agarwal and Taffler, 2008) and default (Sueyoshi and Goto, 2009 and Castagnolo and Ferro, 2014). Altman Z score was applied as a financial performance measurement for companies in East Asia (Allayannis et al., 2003) and for Islamic and conventional banks in Malaysia (Othman, 2013). As dependent variables in models (Sueyoshi and Goto, 2009 and Hogan, 2014). Grice and Ingram (2001) found that Altman's models are useful for predicting financial stress conditions other than bankruptcy.

Thirdly, the majority of Altman's models were employed for industrial and nonfinancial companies and only a few for bank bankruptcy prediction (Vaziri et al., 2012, Rankov and Kotlica, 2013, Chieng, 2013, Othman, 2013, Hogan, 2014 and Pradhan, 2014). Rankov and Kotlica (2013) and Hogan (2014) used the five factor Z score model, whereas Vaziri et al. (2012), Chieng (2013), Othman (2013) and Pradhan (2014) used the Z (1993) four factor model. Vaziri et al. (2012) compared the four factor Z (1993) model for non-manufacturing companies with Moody's, Standard and Poor's and Vaziri's financial ratios, and found that the Z" model gives the superior prediction. Othman (2013) applied the Z (1993) model for evaluation of Malaysian bank performance. Rankov and Kotlica (2013) found that the five factor Z score model could be a base for risk assessment and help in predicting failure. Chieng (2013) suggested that the Z" model is a reliable predictor of bank failure within five years prior to bankruptcy.

Fourthly, some of these studies used the original Altman model (Griffin and Lemmon, 2002, Chava and Jarrow, 2004, Hillegeist et al., 2004, Rankov and Kotlica, 2013 and Othman, 2013). Others re-estimated the Altman models to improve their predictability such as Moyer (1977), Coats and Fant (1993), Begley et al. (1996), Grice and Ingram (2001), Wu et al. (2010) and Ho et al. (2013). The original Z (1993) model performed satisfactorily in an international context. Summarizing their practical applications, in general, the Altman model performs reasonably well and the classification accuracy for some countries could be improved with country-specific estimation. *"In a country model, the information provided even by simple additional variables may help boost the classification accuracy to a much higher level"* (Altman et al., 2014, p.19).

Moreover, Altman (2014) noted that the most important changes in the modification of the Z-Score Model are the updating of financial data in order to re-estimate variables and the usage of other estimation techniques in order to improve model efficiency. Researchers who widely applied these changes saw improvement in the model performance and predictability (Moyer, 1977, Merkevicius et al., 2006, Wu et al., 2010 and Ho et al., 2013). For example, Moyer (1977) increased the predictability of Altman's model from 75% to 88.1% by re-estimating it with the Direct method and to 90.48% with the Wilks method. Ho et al. (2013) used Altman's model for a robustness check and decreased the misclassification errors from 30% for the original model to 7% with the re-estimated model. This study contributes to the literature by updating previous researchers' findings and outlining the considerable body of results from the re-estimated Altman models for bankruptcy prediction.

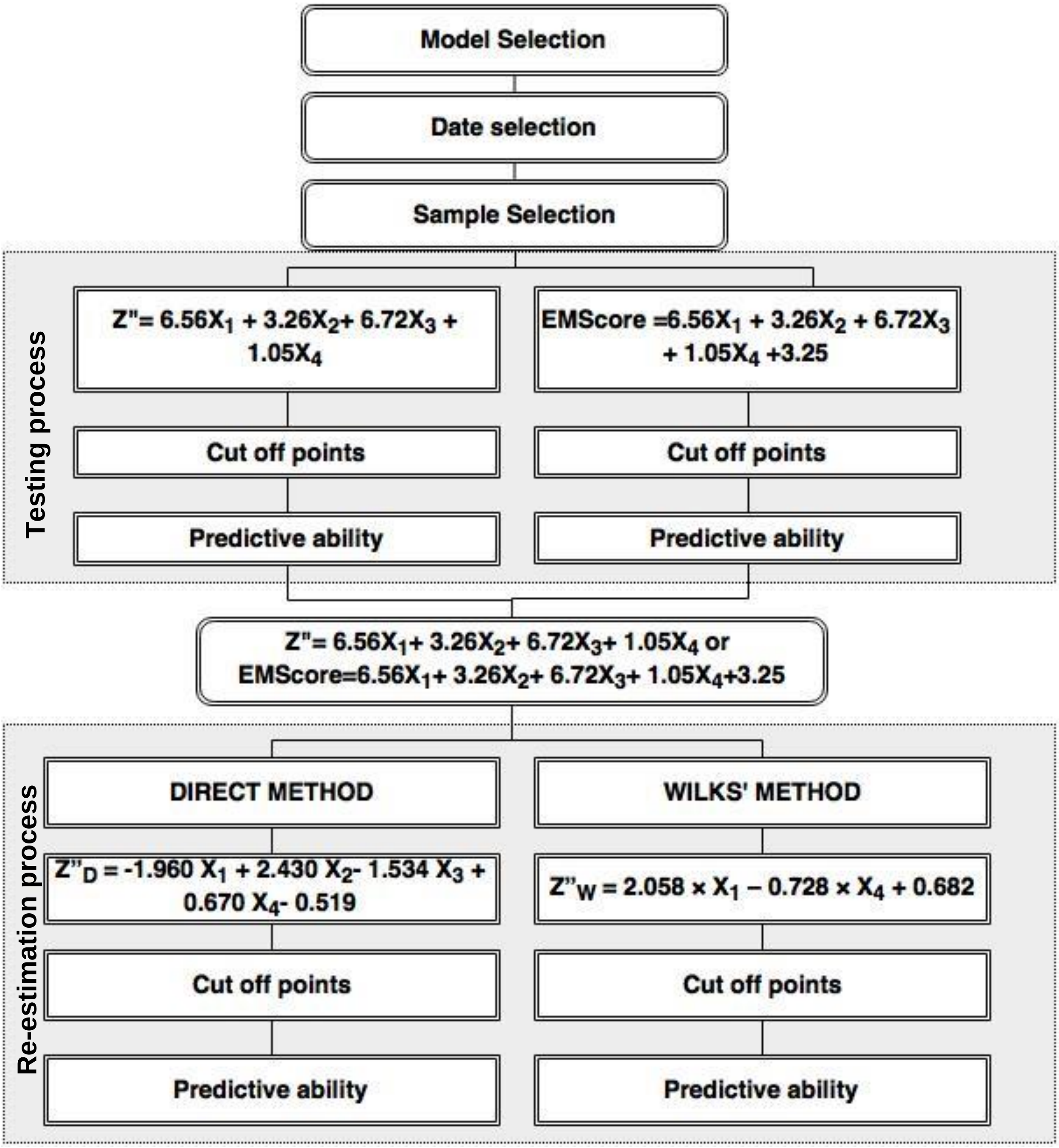
Firstly, the literature survey shows Altman's models were employed not only for prediction of bankruptcy but also for failure, distress and default. This study will use Altman's models as it assumes that they are able to forecast financial unsoundness. Secondly, Altman models are mostly used for company bankruptcy prediction. A few studies consider bank failure and this study aims to fill this gap and employ the Z (1993) four-factor model for non-manufacturing companies' in the case of Kazakhstan banks. Thirdly, this study supplements a number of studies devoted to developing countries with reference to Kazakhstan and uses the EM Score (1995) modification of the Z (1993) model for emerging markets. Lastly, in light of the criticisms of the Altman approach, the above two Altman models will be re-estimated for a given country data in terms of classification accuracy.

### 4.3 Research Process

This chapter examines the second research question of whether Altman's models can adequately predict bank financial unsoundness.

The research process is presented in Figure 4.1 to address this question.

**Figure 4.1: Research Process**




**Source:** Author using draw.io

In the first step of the research process Altman's Z (1993) and EM Score (1995) models were selected. These two models are presented in Table 4.3.

**Table 4.3 Chosen Altman Models**

| Function | Variables | Application Area | Cut-of Scores |
|---|---|---|---|
| Z(1993) = $6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$ | $X_1$ – Working Capital / Total Assets;<br>$X_2$ – Retained Earnings / Total Assets;<br>$X_3$ – EBIT / Total Assets;<br>$X_4$ – Book Value Equity / Book Value of Total Liabilities | Non-manufacturing companies | Bankrupt<1.1< Grey>2.6> Safe |
| EM Score (1995) = $6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + 3.25$ | $X_1$ – Working Capital / Total Assets;<br>$X_2$ – Retained Earnings / Total Assets;<br>$X_3$ – EBIT / Total Assets;<br>$X_4$ – Book Value Equity / Book Value of Total Liabilities | Non-manufacturing companies in Emerging Markets | Bankrupt<1.1< Grey>2.6> Safe |

**Source:** Altman (2000)

All four Altman variables were selected and analysed in Section 3.4.

Secondly, these models were tested on annual data of 12 Kazakhstan banks during the period from 1st January, 2008 to 1st January, 2014 (Appendix 4A).

Thirdly, in the previous chapter two groups of sound and unsound banks were obtained using a cluster-based methodology of financial soundness assessment. The financially unsound banks are BTA Bank, Kazkommertsbank, ATF Bank, Alliance Bank, Temirbank and Nurbank. The government acquired 75% of BTA bank's equity and 20% of Kazkommertsbank's equity. Equity of the Alliance bank was sold by the owners for $1 to the government. The ATF Bank, Temirbank and Nurbank were unable to meet their scheduled payments. In 2015 the BTA Bank merged with Kazkommertsbank and the Alliance Bank and Temirbank merged with Forte bank. Thus, the unsoundness of 6 banks obtained by cluster analysis on 1st January 2014 was established.

The 6 sound banks were selected from a group of financially sound banks based on asset size, specialization and branch network. Thus the sample is composed of 12 banks with a share of assets in the total assets of the banking sector at 81.3% (Table 4.4). These 12 banks represent almost the entire banking sector of Kazakhstan. 84 observations from annual financial reports are used in the analysis.

**Table 4.4: Selected Sample of Banks and Asset Share, 1st January, 2014**

| № | Unsound Bank | Share in Assets of Banking Sector, % | Ranking | Sound Bank | Share in Assets of Banking Sector, % |
|---|---|---|---|---|---|
| 1 | Kazkommertsbank | 16.2 | 1 | Halyk Bank of Kazakhstan | 15.8 |
| 2 | BTA Bank | 9.8 | 2 | Bank Centercredit | 6.9 |
| 3 | ATF Bank | 5.8 | 3 | SB Sberbank | 6.7 |
| 4 | Alliance Bank | 3.6 | 4 | Tsesnabank | 6.0 |
| 5 | Temirbank | 2.0 | 5 | Kaspi Bank | 5.5 |
| 6 | Nurbank | 1.6 | 6 | Bank RBK | 1.4 |
| Total | | 39 | Total | | 42.3 |
| Total of two groups | | | | | 81.3 |

**Source:** Author

The small sample is typical for studies on data on an individual country. In the previous section journal articles with small samples were studied. For example, Othman (2013) investigates 13 Malaysian Islamic and 10 conventional banks; Rankov and Kotlica (2013) examined 10 Serbian banks; Chieng (2013) analyses 4 distressed and 4 control banks from the Eurozone; Pradhan (2014) examines 3 Indian banks. When a sample is small it is impossible to divide it into ‘training’ and ‘holdout’ types. Altman (1995a) noted that, in the case of a lack of observations, it is not possible to test the model on a new meaningful 'holdout' group. Bellovary et al. (2007) reviews bankruptcy prediction studies from 1930 to 2007 and notes that roughly less than half of the studies use hold-out sample.

In this study there is not enough data to allow for testing. That is why a leave-one-out classification is used as a form of cross-validation of the classification table. Under this approach, a discriminant function based on all cases except the selected example is used to classify this case (Nasledov, 2013).

Fourth, as seen from Table 4.3, these two models differ by a constant at 3.25, with the same variables and cut off points. To assess the probability of bankruptcy for both Altman’s Z” and EM Score models, cut off points are proposed where a value of less than 1.1 gives a high probability of bankruptcy; 1.10 to 2.6 is ‘grey zone’ and gives a distress situation; and a value equal to or more than 2.6 gives a low probability of bankruptcy. This study, as was mentioned above, focused on bank financial unsoundness, which is the earlier step of distress and not bankruptcy (Section 4.2.1). Therefore, a value less than 2.6 classifies a bank as unsound and a value higher than 2.6 will rate a bank as sound. A ‘grey zone’ will be clearly interpreted as unsound.

In order to improve the predictability of Altman's models, a technique from Wu et al. (2010) is adapted. The obtained Z (1993) and EM Scores (1995) are ranked from lowest to highest. It is assumed that the optimal cutoff point is between 25 and 95 percentiles. The predictability and the Type I and II errors are calculated with the step at 5 percentile within this range. Close to the segment with highest values calculations are made with the step at 1 percentile. A new cutoff point is set for the percentile at which the sum of Types I and II classification errors is minimized.

Finally, Altman's Z model was re-estimated as both the Z (1993) and EM Scores (1995) models consist of four similar variables and differ from each other only by a constant 3.25. The process of re-estimating Altman model is designed according to that of Moyer (1977). The Direct approach includes in the discriminant function each of the four variables specified by Altman. The Wilks' approach enters variables into the function in a stepwise manner up to the point where the Wilks' lambda is minimized. Both approaches will be used to compare their abilities to assess financial unsoundness of banks.

The significance of the re-estimated models is determined by the Wilks' Lambda, the Chi-square and by the statistical significance. The closer is the Wilks' Lambda value to 1, the superior is the model's quality. The Chi-square measure defines the power at which the discriminant function distinguishes between groups. The higher is the value, the greater can the discriminant function distinguishes between groups and the more effectively it fulfills its intended use. Its consistency can be judged by the statistical significance which must be less than 0.05.

In the process of re-estimation the two models of $Z_D$ and $Z_W$ were obtained. For each re-estimated model new cut off points and predictive accuracy were calculated. Othman (2013) noted that the optimum cut-off score is approximately equal to zero and is the weighted average of the discriminant score of the sound and unsound bank groups. If the discriminant score is less than the cut-off score, the bank is classified as unsound and, if the discriminant score is more than the cut-off point, the bank is classified as sound.

### 4.4 Empirical Results of Testing the Altman Models

The process of testing the Altman Models contains four steps. Firstly, for each variable the mean value and standard deviation are calculated and the F and t test are performed. Secondly, based on a selected sample Z (1993), EM Scores (1995) and predicted statuses of sound and unsound banks were estimated. Thirdly, the predicted and assigned status were compared and the predictive accuracy, Type I and Type II errors of the two models were calculated. Finally, new cutoff points were selected to minimize the classification errors and to increase the predictive accuracy.

### 4.4.1 Descriptive statistics

Then the four variables for the sample banks and the mean values and standard deviations of the financial ratios for the two groups (sound and unsound banks) and the significance tests were developed as follows:

A two-sample F-test for variances is used to compare the two mean values. This test is used to check if the variances of the two groups are the same or not where the $H_0$ is $\sigma1=\sigma2$. Based on the F test result then the appropriate t test to compare the means is chosen.

If the p value from the F test is smaller than 0.05, the $H_0$ is rejected and the T test assuming unequal variance is used. If the p value from F is higher than 0.05, the $H_0$ cannot be rejected and the t test assuming equal variance is used.

The F and T test of the equality of group means for each ratio are presented in Table 4.5.

**Table 4.5: Analysis of Group Means for Independent Variables**

| | Sound | | Unsound | | F test | | T test | |
|---|---|---|---|---|---|---|---|---|
| | Mean | St. Dev | Mean | St. Dev | F value | (p value) | t value | (p value) |
| X1: Working Capital / Total Assets | -0.309 | 0.576 | -0.061 | 0.342 | 2.834 | 0.001 | -2.398 | 0.010 |
| X2: Retained Earnings / Total Assets | 0.011 | 0.014 | -0.047 | 0.313 | 0.002 | 0.000 | 1.192 | 0.120 |
| X3: EBIT / Total Assets | 0.068 | 0.032 | 0.033 | 0.293 | 0.012 | 0.000 | 0.771 | 0.223 |
| X4: Book Value Equity / Book Value of Total Liabilities | 0.692 | 1.767 | 0.135 | 0.164 | 116.73 | 0.000 | 2.031 | 0.021 |

**Source:** Author

Table 4.5 shows how great the variance of variable-predictor values in the two groups is. In the period from 1st January, 2008 to 1st January, 2014 the working capital to total assets ratio for unsound banks was lower than for sound banks. The working capital to total assets ratio was -30.9% for sound banks and -6.1% for unsound banks. The retained earnings to total assets were 1.1% for sound and -4.7% for unsound banks. EBIT to total assets was 6.8% and 3.3% respectively and equity to total liabilities was 69.2% for sound banks and 13.5% for unsound banks.

For all variables the p values of F test are smaller than 0.05. $H_0$ is rejected that is why the t test assuming unequal variance was selected. T test p values of $X_1$ and $X_4$ was smaller than 0.05 indicating a tendency towards the significance of the difference between the two groups. T test p values of $X_2$ and $X_3$ is higher than 0.05. Indicators $X_2$ and $X_3$ are insignificant for the discriminant analysis.

### 4.4.2 Testing of Altman Models

All Altman variables were taken for further testing and for calculating the values of Z (1993) and EM Scores (1995) according to the formulae given in Table 4.3. The results of the calculations, the assigned and predicted statuses are summarized in Appendix 4B. As mentioned above, the cut off point for unsoundness prediction of both Altman models is 2.6. Values which are less than 2.6 are interpreted as unsound and a value that is higher than 2.6 indicates sound banks.

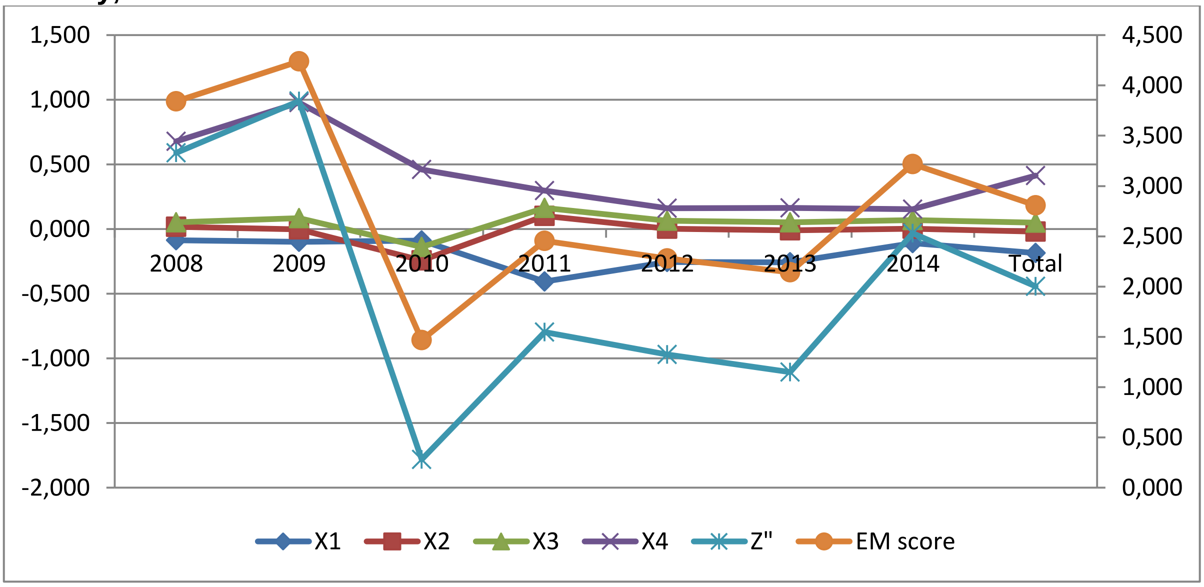
Based on Appendix 4A, the mean values of Z (1993) and EM Scores (1995), as well as the mean indicators $X_1$, $X_2$, $X_3$ and $X_4$ for all Kazakhstan banks, have been calculated annually. They are summarized in Table 4.6 and Figure 4.2.

**Table 4.6: Mean Values of Individual Coefficients, Z" and EM Score of Banks from 1st January, 2008 to 1st January, 2014**

| Date | $X_1$ | $X_2$ | $X_3$ | $X_4$ | Z» | EM Score |
|---|---|---|---|---|---|---|
| 2008 | -0.086 | 0.018 | 0.053 | 0.679 | 0.591 | 3.841 |
| 2009 | -0.098 | -0.001 | 0.086 | 0.979 | 0.991 | 4.241 |
| 2010 | -0.089 | -0.242 | -0.137 | 0.461 | -1.781 | 1.469 |
| 2011 | -0.406 | 0.103 | 0.164 | 0.298 | -0.796 | 2.454 |
| 2012 | -0.253 | 0.003 | 0.065 | 0.161 | -0.969 | 2.281 |
| 2013 | -0.256 | -0.009 | 0.052 | 0.165 | -1.106 | 2.144 |
| 2014 | -0.107 | 0.003 | 0.070 | 0.153 | -0.031 | 3.219 |
| Total | -0.185 | -0.018 | 0.050 | 0.414 | -0.443 | 2.807 |

**Source:** Author

**Figure 4.2: Mean Values of Variables for Altman Model from 1st January, 2008 to 1st January, 2014**




**Source:** Author

It can be seen from Table 4.6 and Figure 4.2 that the most significant indicator for the Altman Z (1993) and EM Scores (1995) is $X_4$ (book value equity / book value of total liabilities). The pattern of the curves for Z (1993) and EM Scores (1995) partly repeat that of the curve for $X_4$. This ratio indicates the dependence of a bank on creditors, on a rise in interest rates and on borrowing conditions the higher is this indicator, the more financially stable is the bank. For the analysed period this indicator was stable and varied from 15.3% to 99.1%.

The shapes of the curves of $X_2$ and $X_3$ repeat each other. Furthermore, the ratios $X_2$ of Retained Earnings/Total Assets and $X_3$ of EBIT/Total Assets measure the ability of banks to generate profit from the sale of their financial services, as well as from the use of their assets. The ratio $X_2$ of cumulative profitability is the ratio of retained earnings to total assets. The ratio $X_3$ of the return on assets is measured as the ratio of earnings before interest and taxes to total assets. The ratio $X_2$ characterizes the long-term profitability and $X_3$ current profitability. The ratio $X_2$ shows the minimum profitability for the entire period under review: on 1st January, 2009, 1st January, 2010 and 1st January, 2013 the values were negative at -0.1%, -24.2% and -0.9%, respectively. The values of ratio $X_3$ were higher than $X_2$, ranging from -13.7% to 16.4% during the period under review.

This ratio $X_1$ measures the ability of banks to meet their obligations at the expense of short-term assets. An increase in the indicator points to an improvement of the liquidity. A low level or decline suggests that perhaps the bank has excessive short-term liabilities. The more effectively the bank operates its working capital, the less it needs to rely on external borrowings. $X_1$ had a negative value during the period under review from 1st January, 2008 to 1st January, 2014.

Next, the performance of Altman Z (1993) and EM Scores (1995) models to predict financial soundness of Kazakhstan banks was assessed (Appendix 4B).

**Table 4.7: Classification of Results of Z and EM Score Models**

| | | Z” | | EM Score | |
| --- | --- | --- | --- | --- | --- |
| Assigned status | | Predicted Group Membership | | Predicted Group Membership | |
| | | Sound | Unsound | Sound | Unsound |
| | Sound | 5 | 37 | 21 | 21 |
| | Unsound | 9 | 33 | 26 | 16 |
| | | 14 | 70 | 47 | 37 |

**Source:** Author

As seen from Table 4.7 in total for the Z (1993) model, the vast majority of observations at 70 were predicting financial unsoundness and only 14 financial soundness. For the EM Score model conversely only 37 observations were predicting financial unsoundness and 47 - financial soundness. The difference between the results from two models is quite obvious.

The accuracy of prediction is estimated by the probability of Type I and II errors for Z (1993) and EM Scores (1995) (Table 4.8).

**Table 4.8: Error Classification for the Altman Z (1993) and EM Scores (1995) Models**

| | Z | | | | EM Score | | | |
|---|---|---|---|---|---|---|---|---|
| Type of Error | Number Correct | % Correct | % Error | Total Observations | Number Correct | % Correct | % Error | Total Observations |
| Type I | 33 | 78.57 | 21.43 | 42 | 16 | 38.10 | 61.90 | 42 |
| Type II | 5 | 11.91 | 98.68 | 42 | 21 | 50.00 | 50.00 | 42 |
| Total | 38 | 45.24 | 54.76 | 84 | 37 | 44.1 | 55.9 | 84 |

**Source:** Author

The Type I errors for the Z (1993) model were 21.43% and the Type II errors 98.69%. A total of 45.24% of observations are correctly classified. In general, the predictability of the Z (1993) Altman model for Kazakhstan banks is low. The Type I errors for the EM Score (1995) model were 61.90% and Type II errors 50.00%. A total of 44.1% of observations are correctly classified. In general, the predictability of Altman's EM Score (1995) model for Kazakhstan banks is low.

These results were obtained using original cutoff points. To improve the predictability of these models, a technique from Begley et al. (1996) and Wu et al. (2010) was employed. The Z (1993) and EM Scores (1995) were ranked from lowest to highest. It was assumed that the superior cutoff point is between 25 and 95 percentiles. For predictability, the Type I and II errors were calculated for all percentiles within this range with the step at 5 percentile. Since the highest values were at 90 percentile, in this segment between 90 and 95 percentiles calculations were made with the step at 1 percentile. Bold font was used to report the point at which the sum of Types I and II classification errors is minimized.

It is important to underline that for predictability, Type I and Type II errors of the Z (1993) and EM Scores (1995) models are equal for the same percentile because the two differ only by a constant 3.25 (Table 4.9).

**Table 4.9: Cutoff Points of Altman's, Z (1993) and EM Scores (1995) Models**

| Model Score (percentile) | Cutoff point Z" | Cutoff point EM Score | For Z" and EM Score | | |
|---|---|---|---|---|---|
| | | | Prediction accuracy | Type I | Type II |
| 25 | -3.240 | 0.010 | 36.90% | 88.10% | 38.10% |
| 30 | -2.677 | 0.573 | 36.90% | 83.33% | 42.86% |
| 35 | -2.022 | 1.228 | 42.86% | 71.43% | 42.86% |
| 40 | -1.543 | 1.707 | 42.86% | 66.67% | 47.62% |
| 45 | -0.534 | 2.716 | 42.86% | 61.90% | 52.38% |
| 50 | -0.321 | 2.929 | 45.24% | 54.76% | 54.76% |
| 55 | 0.000 | 3.250 | 47.62% | 47.62% | 57.14% |
| 60 | 0.207 | 3.457 | 42.86% | 47.62% | 66.67% |
| 65 | 0.693 | 3.943 | 40.48% | 45.24% | 73.81% |
| 70 | 1.085 | 4.335 | 39.29% | 40.48% | 80.95% |
| 75 | 1.692 | 4.942 | 41.67% | 33.33% | 83.33% |
| 80 | 2.391 | 5.641 | 44.05% | 26.19% | 85.71% |
| 85 | 2.713 | 5.963 | 46.43% | 19.05% | 88.10% |
| 89 | 3.324 | 6.574 | 47.62% | 14.29% | 90.48% |
| 90 | 3.347 | 6.597 | 48.81% | 11.90% | 90.48% |
| 91 | 3.390 | 6.640 | 50.00% | 9.52% | 90.48% |
| 92 | 3.856 | 7.106 | 51.19% | 7.14% | 90.48% |
| **93** | **4.649** | **7.899** | **52.38%** | **4.76%** | **90.48%** |
| 94 | 4.827 | 8.077 | 51.19% | 4.76% | 92.86% |
| 95 | 6.688 | 9.938 | 51.19% | 4.76% | 92.86% |

**Source:** Author

Table 4.9 shows that for the two models the sum of the classification errors is minimized with a cutoff point between the 90th and 95th percentiles. Total classification error rates are minimized by classifying as unsound only those banks with Z (1993) and EM Scores (1995) results under the 93th percentile. Wu et al. (2010) noted that minimizing the sum of Type I and Type II errors is not necessarily optimal. From a regulatory point of view Type I errors are more costly than Type II errors. This may motivate regulator to move cutoff values to reduce Type I errors.

The results of the calculations and assigned and predicted statuses of the Z (1993) and EM Scores (1995) Models with new cutoff points are summarized in Appendix 4C. As was mentioned above cut off points for the unsoundness prediction of the Altman's Z (1993) model is at 4.649 and of the Altman EM Score (1995) at 7.899. The values that are less than cutoff points were interpreted as unsound and a value higher as sound.

Based on Appendix 4C a summary of the new classification of results is provided in Table 4.10.

**Table 4.10: Classification of Results of Altman's Models for Banks from 1st January, 2008 to 1st January, 2014 with Cutoff Points at 93 percentile**

| Predicted status | Z and EM Score |
|---|---|
| Unsound | 40 |
| Sound | 4 |
| Total | 44 |

**Source:** Author

As seen from Table 4.10 in total for the Z (1993) and EM Scores (1995) models 40 observations were predicting financial unsoundness and 4 financial soundness.

The comparison of the predicted values of the dependent variable calculated according to the four-factor Z (1993) and EM Scores (1995) models with new cutoff points and the actual observed values are shown in Table 4.11.

**Table 4.11: Classification of Results of Z (1993) and EM Scores (1995) Models with Cutoff Point at 91 percentile**

| | | Z and EM Score | |
|---|---|---|---|
| | | Predicted Group Membership | |
| | | Sound | Unsound |
| Assigned status | Sound | 4 | 38 |
| | Unsound | 2 | 40 |
| | | 6 | 78 |

**Source:** Author

The accuracy of prediction is estimated by the probability of Type I and II errors for the Z (1993) and EM Scores (1995) models with new cutoff points (Table 4.12).

**Table 4.12: Error Classification for Altman's Z (1993) and EM Scores (1995) Models with Cutoff Point at 93 percentile**

| | Z and EM Score for 93 percentile | | | |
|---|---|---|---|---|
| Type of Error | Number Correct | % Correct | % Error | Total Observations |
| Type I | 40 | 95.24 | 4.76 | 42 |
| Type II | 4 | 9.52 | 90.48 | 42 |
| Total | 44 | 52.38 | 47.62 | 84 |

**Source:** Author

As depicted in this section, the two original Altman models have low predictability in the observed period. In the Z (1993) model the Type II errors prevail over Type I errors while in the EM Score (1995) model Type I errors dominate with the original cutoff point. Even with new cutoff points these models demonstrate predictability at 52.38% and Type I errors at 4.76% and

Type II at 90.48%.

Popov and Kadyrov (2014) argue that for the successful application of the Altman model outside USA, it is necessary to re-estimate the weights of variables considering the specific factors of a national economy. This has led to a further re-estimation of the coefficients of Altman's models using a selected sample of banks in the next section.

### 4.5 Empirical Results of Re-estimated Altman Models

In the previous section, the original Altman models showed a high level of Type I and Type II errors and modest predictability. In order to improve the results of the predictability of Altman's model, it was decided to re-estimate them. Joy and Tollefson (1975, 1978), Moyer (1977), Grice and Dugan (2003) noted the following reasons for re-estimation:

- the models were developed using samples from the 1970s, where there is limited evidence addressing the sensitivity of these models to time periods, financial distress situations, and industries outside those of the original samples;
- the construct validity of the financial distress/bankruptcy proxies (based on the original models) used in those recent studies is possibly open to question;
- the original Altman model included some inappropriate variables.

Two Altman's the Four-Factor Z Model (1993) for non-manufacturing companies and the Four-Factor EM Score Model (1995) for Emerging Markets are re-estimated using the Direct method and the Wilk's method. The Direct method includes all four variables from Altman's model in the discriminant function. The Wilk's method enters variables into the function in a stepwise manner up to the point where the Wilks' lambda is minimized. In the equation, there are alternately introduced the predictors based on the preset inclusion criterion (by default, the criterion is $F \geq 3.84$) and excluded are the predictors that satisfy the criterion of exclusion (by default, such criterion is $F \leq 2.71$). The reason for using both the Direct and Wilk's methods is that, by comparing the two results, it is possible to gain insight about the necessity for including all four variables in the model.

In fact, only the Altman Z (1993) models re-estimated, because re-estimated the two Altman models differ from each other only by a constant 3.25, where all four variables are similar.

#### 4.5.2 Re-estimation by Direct Method

A test of significance of the differences between the variables in both groups was carried out; along with the test value, the Wilks' Lambda which is a simple variance analysis was also used (Table 4.13). For the variables $X_1$ and $X_4$ the value of F is greater than 3.81, indicating a tendency towards the significance of the difference between the two groups, where $X_2$ and $X_3$ has the value of F lower than 3.81.

**Table 4.13: Tests of Equality of Group Means**

| | Wilks' Lambda | F | df1 | df2 | Sig. |
|---|---|---|---|---|---|
| $X_1$ | 0.934 | 5.749 | 1 | 82 | 0.019 |
| $X_2$ | 0.983 | 1.421 | 1 | 82 | 0.237 |
| $X_3$ | 0.993 | 0.594 | 1 | 82 | 0.443 |
| $X_4$ | 0.952 | 4.127 | 1 | 82 | 0.045 |

**Source:** Author

In the Function column of Table 4.14 the value "1" indicates that one discriminant function was obtained in the course of the discriminant analysis. If the dependent variable had not two but three levels, two discriminant functions would be composed.

**Table 4.14: Eigenvalues**

| Function | Eigenvalue | % of Variance | Cumulative % | Canonical Correlation |
|---|---|---|---|---|
| 1 | 0.228[a] | 100.0 | 100.0 | 0.431 |

a. First 1 canonical discriminant functions were used in the analysis.

**Source:** Author

The low Eigenvalue (0.228) indicates that the obtained model has a low possibility of discrimination. In addition, the low index of canonical correlation (0.431) suggests a weak relationship with the variables that define this index.

Table 4.15 - Wilks' Lambda lists the indicators that determine the significance of the model obtained because of discriminant analysis.

**Table 4.15: Wilks' Lambda**

| Test of Function(s) | Wilks' Lambda | Chi-square | Df | Sig. |
|---|---|---|---|---|
| 1 | 0.814 | 16.455 | 4 | 0.002 |

**Source:** Author

Wilks' Lambda at 0.814 indicates an insufficient level of discrimination.

The lower is the value of Chi-square, the weaker the discriminant function distinguishes between groups and the less effectively it fulfills its intended use. In this case it is 16.455. Its consistency is demonstrated by the statistical significance Sig., which in this case is 0.002 and lower than 0.05.

**Table 4.16: Standardized Canonical Discriminant Function Coefficients**

| | Function |
|---|---|
| | 1 |
| $X_1$ | -0.928 |
| $X_2$ | 0.538 |
| $X_3$ | -0.320 |
| $X_4$ | 0.840 |

**Source:** Author

Table 4.16 of the Standardized Canonical Discriminant Function Coefficients and Table 4.17 of the Structure Matrix make it possible to assess the correlation of individual independent variables used in the discriminant function with the standardized coefficients.

**Table 4.17: Structure Matrix**

| | Function |
|---|---|
| | 1 |
| $X_3$ | -0.554 |
| $X_4$ | 0.469 |
| $X_2$ | 0.275 |
| $X_1$ | 0.178 |

**Source:** Author

As can be seen from the Table 4.17 variables $X_1$ have low correlation coefficients at 0.178.

Further, the discriminant function coefficients are calculated and the discriminant equation is derived based on them. They are included in Table 4.18.

**Table 4.18: Canonical Discriminant Function Coefficients**

| | Function |
|---|---|
| | 1 |
| $X_1$ | -1.960 |
| $X_2$ | 2.430 |
| $X_3$ | -1.534 |
| $X_4$ | 0.670 |
| (Constant) | -0.519 |

**Source:** Author

The discriminant function equation has the form:

$$Z_D = -1.960\ X_1 + 2.430\ X_2 - 1.534\ X_3 + 0.670\ X_4 - 0.519 \qquad (4.1)$$

The Functions at Group Centroids list the mean values of the discriminant function in each of the analyzed group of dependent variable.

**Table 4.19: Functions at Group Centroids**

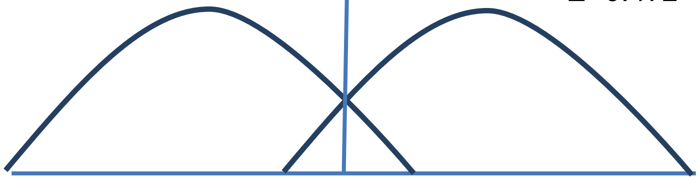
| Status | Function 1 |
|---|---|
| Sound | 0.472 |
| Unsound | -0.472 |

Unstandardized canonical discriminant functions evaluated at group means.

**Source:** Author using SPSS

Since the sample is symmetrical the cutoff point is 0.

**Figure 4.3: Cut Off Point for $Z_D$**




**Source:** Author

If $Z_D < 0$ a bank is predicted as financially unsound and if $Z_D > 0$ a bank is financially sound. Now, based on this equation and the cut off points, the probability that a bank will become financial unsound is calculated (Appendix 4D).

The classification results are summarized in Table 4.20, where the final line provides information on the accuracy of predictions.

**Table 4.20: Classification of Results of the Re-estimated Altman Model, $Z_D$**

| Status | | | Predicted Group Membership | | Total |
|---|---|---|---|---|---|
| | | | Sound | Unsound | |
| Original | Count | Sound | 24 | 18 | 42 |
| | | Unsound | 13 | 29 | 42 |
| | % | Sound | 57.1 | 42.9 | 100.0 |
| | | Unsound | 31.0 | 69.0 | 100.0 |
| Cross-validated[b] | Count | Sound | 23 | 19 | 42 |
| | | Unsound | 14 | 28 | 42 |
| | % | Sound | 54.8 | 45.2 | 100.0 |
| | | Unsound | 33.3 | 66.7 | 100.0 |

a. 63.1% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 60.7% of cross-validated grouped cases correctly classified.

**Source:** Author

The overall accuracy of predictions is 63.1% while the cross-validated result is lower at 60.7%. Table 4.21 presents the classification of errors.

**Table 4.21: Classification of Errors of the Re-estimated Altman's $Z_D$ Model,**

| Type of error | Number correct | % correct | % error | Total observations |
|---|---|---|---|---|
| Type I | 29 | 69.05 | 30.95 | 42 |
| Type II | 24 | 57.14 | 42.86 | 42 |
| Total | 53 | 63.10 | 36.90 | 84 |

**Source:** Author

The results of the Re-estimation of the Altman model by the Direct method in Table 4.21 show that Type I errors in the model were 30.95% and Type II errors 42.86%. The overall accuracy of prediction is 63.1% in the original sample and 60.71% in the cross validated sample that can be considered as low.

### 4.5.3 Re-estimation: Wilks' method

In Table 4.22 are presented variables entered in the model. The re-estimated model has only two variables $X_1$ and $X_4$. Variables $X_2$ and $X_3$ were removed from the model as insignificant.

**Table 4.22: Variables Entered/Removed[a,b,c,d]**

| | | Wilks' Lambda | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | | Exact F | | | |
| Step | Entered | Statistic | df1 | df2 | df3 | Statistic | df1 | df2 | Sig. |
| 1 | $X_1$ | 0.934 | 1 | 1 | 82.000 | 5.749 | 1 | 82.000 | 0.019 |
| 2 | $X_4$ | 0.823 | 2 | 1 | 82.000 | 8.680 | 2 | 81.000 | 0.000 |

At each step, the variable that minimizes the overall Wilks' Lambda is entered.

a. Maximum number of steps is 8.

b. Minimum partial F to enter is 3.84.

c. Maximum partial F to remove is 2.71.

d. F level, tolerance, or VIN insufficient for further computation.

**Source:** Author

Next, Table 4.23 shows the canonical correlation coefficient for this study, which is low at 0.420. That suggests weak correlation with the variables that define this index.

**Table 4.23: Eigenvalues**

| Function | Eigenvalue | % of Variance | Cumulative % | Canonical Correlation |
|---|---|---|---|---|
| 1 | 0.214[a] | 100.0 | 100.0 | 0.420 |

**Source:** Author

Also a high Wilks' Lambda at 0.823 indicates an insufficient level of discrimination (Table 4.24)

**Table 4.24: Wilks' Lambda**

| Test of Function(s) | Wilks' Lambda | Chi-square | df | Sig. |
|---|---|---|---|---|
| 1 | 0.823 | 15.730 | 2 | 0.000 |

**Source:** Author

Next, canonical discriminant function coefficients are calculated and analyzed (Table 4.25).

**Table 4.25: Canonical Discriminant Function Coefficients**

| | Function |
|---|---|
| | 1 |
| X1 | 2.058 |
| X4 | -0.728 |
| (Constant) | 0.682 |

Unstandardized coefficients

**Source:** Author

As a result, given the constant, the discriminant function equation has the form:

$$Z_W = 2.058 \times X_1 - 0.728 \times X_4 + 0.682 \qquad (4.2)$$

Table 4.26 lists the mean values of the discriminant function in each of the analyzed group of dependent variable.

**Table 4.26: Functions at Group Centroids**

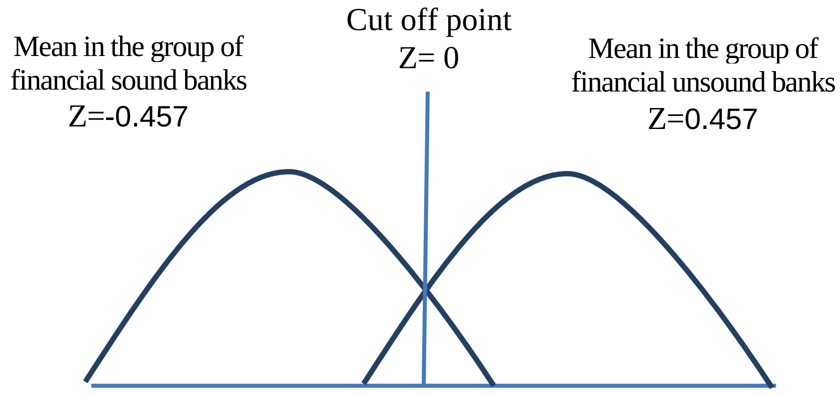
| Status | Function |
|---|---|
| | 1 |
| Sound | -0.457 |
| Unsound | 0.457 |

Unstandardized canonical discriminant functions evaluated at group means.

**Source:** Author using SPSS

Since the sample is symmetrical the cutoff point is 0.

**Figure 4.4: Cut Off Point for $Z_W$**




**Source:** Author

If $Z_W < 0$ a bank is predicted as financial sound and if $Z_W > 0$ a bank is financial unsound. Now, based on this equation and cut off points, the probability that a bank will become financial unsound can be calculated (Appendix 4E).

The classification results are summarized in Table 4.27, where the final line provides information on the accuracy of predictions.

**Table 4.27: Classification of Results of the Re-estimated Altman $Z_W$ [a] Model**

| Default | | | Predicted Group Membership | | Total |
|---|---|---|---|---|---|
| | | | Sound | Unsound | |
| Original | Count | Sound | 24 | 18 | 42 |
| | | Unsound | 14 | 28 | 42 |
| | % | Sound | 57.1 | 42.9 | 100.0 |
| | | Unsound | 33.3 | 66.7 | 100.0 |
| Cross-validated[b] | Count | Sound | 24 | 18 | 42 |
| | | Unsound | 14 | 28 | 42 |
| | % | Sound | 57.1 | 42.9 | 100.0 |
| | | Unsound | 33.3 | 66.7 | 100.0 |

a. 61.9% of original grouped cases correctly classified.
b. Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
c. 61.9% of cross-validated grouped cases correctly classified.
**Source:** Author

The overall accuracy of predictions is 61.9% and is the same for the original grouped cases and for the cross-validated cases. Table 4.28 presents the classification of errors.

**Table 4.28: Classification of Errors of the Re-estimated Altman $Z_W$ Model**

| Type of error | Number correct | % correct | % error | Total observations |
|---|---|---|---|---|
| Type I | 28 | 66.67 | 33.33 | 42 |
| Type II | 24 | 57.14 | 42.86 | 42 |
| Total | 52 | 61.90 | 38.10 | 84 |

**Source:** Author

The results of the Re-estimation of the Altman model by the Wilk's method in Table 4.28 show that Type I errors in the model were 33.33% and Type II errors 42.86%. The overall accuracy of predictions is 61.9% and that can be considered as low.

Now, new cutoff points are selected for the re-estimated models as it was done in the previous section for the original models using percentile. The obtained $Z_D$ and $Z_W$ results were ranked from lowest to highest. It was assumed that the superior cutoff point is between 25 and 95 percentiles. For predictability, the Type I and II errors were calculated for all percentiles within this range with the step at 5 percentile. In this segment between the highest values calculations were made with the step at 1 percentile. Bold font was used to highlight the point at which the sum of Types I and II classification errors is minimized (Table 4.29).

**Table 4.29: Cut off points of the Re-estimated Altman Models, $Z_D$ and $Z_W$**

| Percentile | $Z''_D$ | Predictability | Type I | Type II | $Z''_W$ | Predictability | Type I | Type II |
|---|---|---|---|---|---|---|---|---|
| 25 | -0.619 | 65.48% | 59.52% | 9.52% | -0.640 | 67.86% | 7.14% | 57.14% |
| 26 | -0.583 | 66.67% | 57.14% | 9.52% | -0.629 | 66.67% | 9.52% | 57.14% |
| 27 | -0.557 | 67.86% | 54.76% | 9.52% | -0.624 | 67.86% | 9.52% | 54.76% |
| 28 | -0.547 | 66.67% | 54.76% | 11.90% | **-0.606** | **69.05%** | **9.52%** | **52.38%** |
| 29 | -0.545 | 67.86% | 52.38% | 11.90% | -0.551 | 67.86% | 11.90% | 52.38% |
| 30 | -0.542 | 67.86% | 52.38% | 11.90% | -0.541 | 67.86% | 11.90% | 52.38% |
| 31 | -0.538 | 69.05% | 50.00% | 11.90% | -0.458 | 69.05% | 11.90% | 50.00% |
| 32 | -0.525 | 67.86% | 50.00% | 14.29% | -0.387 | 67.86% | 14.29% | 50.00% |
| 33 | -0.508 | 66.67% | 50.00% | 16.67% | -0.321 | 66.67% | 16.67% | 50.00% |
| 34 | -0.481 | 67.86% | 47.62% | 16.67% | -0.268 | 65.48% | 19.05% | 50.00% |
| 35 | -0.429 | 66.67% | 47.62% | 19.05% | -0.264 | 64.29% | 21.43% | 50.00% |
| 40 | -0.324 | 61.90% | 47.62% | 28.57% | -0.150 | 61.90% | 28.57% | 47.62% |
| 45 | -0.265 | 59.52% | 45.24% | 35.71% | -0.029 | 61.90% | 33.33% | 42.86% |
| 50 | -0.125 | 61.90% | 38.10% | 38.10% | 0.163 | 61.90% | 38.10% | 38.10% |
| 55 | -0.054 | 61.90% | 33.33% | 42.86% | 0.344 | 59.52% | 45.24% | 35.71% |
| 60 | 0.175 | 61.90% | 28.57% | 47.62% | 0.416 | 59.52% | 50.00% | 30.95% |
| 65 | 0.298 | 66.67% | 19.05% | 47.62% | 0.517 | 64.29% | 50.00% | 21.43% |
| 70 | 0.481 | 70.24% | 9.52% | 50.00% | 0.599 | 67.86% | 52.38% | 11.90% |
| 71 | 0.538 | 70.24% | 9.52% | 50.00% | 0.603 | 67.86% | 52.38% | 11.90% |
| 72 | 0.551 | 69.05% | 9.52% | 52.38% | 0.611 | 66.67% | 54.76% | 11.90% |
| 73 | 0.589 | 67.86% | 9.52% | 54.76% | 0.638 | 67.86% | 54.76% | 9.52% |
| 74 | 0.627 | 69.05% | 7.14% | 54.76% | 0.655 | 66.67% | 57.14% | 9.52% |
| **75** | **0.655** | **70.24%** | **4.76%** | **54.76%** | 0.672 | 65.48% | 59.52% | 9.52% |
| 76 | 0.684 | 69.05% | 4.76% | 57.14% | 0.719 | 66.67% | 59.52% | 7.14% |
| 77 | 0.697 | 69.05% | 4.76% | 57.14% | 0.725 | 66.67% | 59.52% | 7.14% |
| 80 | 0.761 | 67.86% | 2.38% | 61.90% | 0.804 | 65.48% | 64.29% | 4.76% |
| 85 | 0.896 | 63.10% | 2.38% | 71.43% | 1.072 | 60.71% | 73.81% | 4.76% |
| 89 | 1.041 | 61.90% | 0.00% | 76.19% | 1.212 | 59.52% | 78.57% | 2.38% |
| 90 | 1.047 | 60.71% | 0.00% | 78.57% | 1.253 | 58.33% | 80.95% | 2.38% |
| 95 | 1.434 | 55.95% | 0.00% | 88.10% | 1.377 | 44.05% | 100.00% | 11.90% |

**Source:** Author

Table 4.29 shows that, for the two re-estimated models of $Z_D$ and $Z_W$ , the sum of the classification errors is minimized with a cutoff point between the 25th and 95th percentiles. Total classification error rates are minimized by classifying as unsound only those banks with $Z_D$ at 75th and $Z_W$ at 28th percentile.

The results of the calculations and assigned and predicted statuses of $Z_D$ and $Z_W$ with new cutoff points are summarized in Appendix 4F. As was mentioned above cut off points for the unsoundness prediction of the $Z_D$ Altman model is at 0.655 and for the $Z_W$ Altman model is -0.606. The values less than the cutoff points were interpreted as unsound and a value higher as sound.

Based on Appendix 4F a summary of the new classification of results is provided in Table 4.30.

**Table 4.30: Classification of Results of the Re-estimated Altman $Z_D$ and $Z_W$ Models**

| $Z_D$ for 75 percentile | | | | |
|---|---|---|---|---|
| Default | | Predicted Group Membership | | Total |
| | | Sound | Unsound | |
| Original | Sound | 19 | 23 | 42 |
| | Unsound | 2 | 40 | 42 |
| | | 21 | 63 | 84 |
| $Z_W$ for 28 percentile | | | | |
| Default | | Predicted Group Membership | | Total |
| | | Sound | Unsound | |
| Original | Sound | 20 | 22 | 42 |
| | Unsound | 4 | 38 | 42 |
| | | 24 | 60 | 84 |

**Source:** Author

Table 4.31 presents the classification of errors.

**Table 4.31: Classification of Errors of the Re-estimated Altman $Z_D$ and $Z_W$ Models**

| Type of error | $Z_D$ for 75 percentile | | | | $Z_W$ for 28 percentile | | | |
|---|---|---|---|---|---|---|---|---|
| | Number correct | % correct | % error | Total observations | Number correct | % correct | % error | Total observations |
| Type I | 40 | 95.24 | 4.76 | 42 | 38 | 90.48 | 9.52 | 42 |
| Type II | 19 | 45.24 | 54.76 | 42 | 20 | 47.62 | 52.38 | 42 |
| Total | 59 | 70.24 | 29.76 | 84 | 58 | 69.05 | 30.95 | 84 |

**Source:** Author

According to Table 4.31 the overall accuracy of predictions for the $Z_D$ model with a new cutoff point increased from 63.1% to 70.24% and for $Z_W$ from 61.9% to 69.05%. New cutoff points also reduced the Type I errors for both models from 30.95% to 4.76% for $Z_D$ and from 33.33% to 9.52% for $Z_W$. At the same time Type II errors increased for these two models.

In this study the original Z and EM Score models of Altman showed poor ability to predict financial unsoundness. Many researchers such as Moyer (1977), Grice and Ingram (2001) and Altman (2014) suggest the need to re-estimate Altman models to decrease their errors. The results of the re-estimated $Z_D$ and $Z_W$ models showed a higher predictive power, but it is not enough to say that they can serve as a reliable and efficient tool for the prediction of bank financial unsoundness. Results of the study show that the ability of the original and re-estimated Altman models to accurately classify banks as being financially unsound is weaker than that reported by Altman (2000). Also, Moyer (1977) testing the original Altman model obtained a 75% of prediction accuracy. Further re-estimation increased it to 90.4%. Vaziri et al. (2012) demonstrated that the Z-score model gave the superior prediction result in comparison with other models which varied from 95% in 2009 to 59% in 2001. Chieng (2013) found that the Z score model predicted 100% of bank failures from five years to the year of their demise. In contrast Grice and Ingram (2001) tested and re-estimated the Z score model; the predictive accuracy of the original model was 56.1% and 85.2% for the re-estimated model. However, Wu et al. (2010) proved that the Altman model performed poorly when related to five other compared models with predictability at 28.7%.

### 4.6 Summary

Many research studies have applied and improved the original Altman models in various industries, markets and countries. There are many studies on bankruptcy prediction in USA and other developed countries but few in emerging countries. According to Pradhan (2014) there is no generally accepted model for bankruptcy prediction that takes into account all economic determinants and features.

Altman's original Z model was developed and tested for USA non-manufacturing companies and the EM Score model for Mexican non-manufacturing companies in the 1990s (Altman, 1995). This study tested the Z and EM Score models on Kazakhstan banks for the recent period from 1st January, 2008 to 1st January, 2014. Since the Altman models were used for the prediction of financial unsoundness and not bankruptcy, the cut-off points were changed and a 'grey zone' was joined to a zone of a high probability of bankruptcy. These two zones formed zone of financial unsound banks.

Tests of the Z and EM Score models demonstrated a low level of predictability at 45.2% and 44.1%, respectively. The original cutoff point was changed by percentile, which improved the predictive accuracy to 52.38% for both models and reduced the Type I and Type II errors.

Then, to increase the accuracy of classification the original Altman models were re-estimated by the Direct method and its predictability was improved to 63.1% in the original grouped cases and 60.7% in cross-validated cases. The discriminant function equation re-estimated by the Direct method with changed weights of variables and the constant took the following form:

$$Z_D = -1.960\ X_1 + 2.430\ X_2 - 1.534\ X_3 + 0.670\ X_4 - 0.519 \qquad (4.1)$$

Also Altman's original model was re-estimated by the Wilk's method and its predictability was improved to 61.9% in the original and cross-validated grouped cases. The discriminant function equation re-estimated by the Wilks' method with two remaining variables took the form of:

$$Z_W = 2.058 \times X_1 - 0.728 \times X_4 + 0.682 \qquad (4.2)$$

Cutoff points in the re-estimated $Z_D$ and $Z_W$ models were changed by percentile. New cutoff points improved the predictive accuracy to 70.24% for $Z''_D$ and 69.05% for $Z''_W$. Re-estimation and changes of cutoff points led to a slight improvement in the performance of the Altman models. However, the predictive accuracy of the original and re-estimated models is weaker than the results obtained by recent researchers such as Xu and Zhang (2009), Wu et al. (2010), Vaziri et al. (2012), Othman (2013), Chieng (2013), Ho et al. (2013), Rankov and Kotlica (2013) and Pradhan (2014). Castagnolo and Ferro (2014) examined and found that the Z-score model did not have the statistical power to predict defaults.

In the literature review of this chapter, Altman (2014) noted that his Z- Score Model was used as the measure of distress in 17 studies and as a robustness check in 3 studies from 34 articles published in prominent international journals. This indicates that the models are highly popular and widely used by academicians and practitioners. However, the findings demonstrate that the tested and re-estimated Altman models have a modest ability to predict financial unsoundness in Kazakhstan banks and they should be used cautiously.

Thereby, in this study, the Altman models did not demonstrate positive results and they cannot be proposed as an efficient tool for supervision bodies to predict the financial unsoundness of Kazakhstan banks. Also, not all variables proposed by Altman are significant for the assessment of the financial unsoundness of Kazakhstan banks. As noted above, Altman advised that other estimation techniques should be used in order to improve the model efficiency and predictability (Altman, 2014). The obtained results give ideas an indication of the need to construct new prediction models for financial unsoundness using MDA, logit and probit analyses.

## CHAPTER 5 COMPARATIVE STUDY OF MDA, LOGIT AND PROBIT MODELS


### ABSTRACT

**Purpose –** The 2008 financial crisis has underscored the importance of predicting the financial unsoundness of banks. Previous studies extensively investigated bank failure prediction in developed countries, especially in the USA. Studies on bankruptcy prediction in developing countries in general and in the post-soviet countries, in particular, is limited. The purpose of this research is to improve the predictability of bank financial unsoundness by constructing an integrated model. It employed statistical models such as MDA, logit and probit to predict bank unsoundness for a sample of Kazakhstan banks. Moreover, an integrated model of predicting the financial unsoundness of banks based on MDA, logit and probit analysis was constructed as a reliable tool for the monitoring and supervision of banks' financial status.

**Design/Methodology/Approach –** MDA, logit and probit modelswere constructed for a sample of 12 Kazakhstan banks for the period from 1$^{st}$ January, 2008 to 1$^{st}$ January, 2012. Then obtained models were tested with the data from 1st January, 2013 to 1st January 2014. A set of financial variables which reflect the capital adequacy, asset quality, management, earnings and liquidity of banks were created, MDA, logit and probit models were estimated to predict bank unsoundness. These models were integrated to improve the predictive accuracy.

**Findings –** The MDA, logit and probit models showed high predictive accuracy at 83.3%, 87.5% and 83.3% respectively, Type II errors at 25%, 16.7% and 25.0%, respectively and Type I errors at 8.3% for all three models. Consistent with results from Lennox (1999) and Lin (2009), this study confirmed the superiority of the logit model. The integrated model for predicting bank financial unsoundness showed predictive accuracy at 87.5% and reduced Type I errors to 0% with Type II errors at 25.0%. Type I error occurs when the bank with a prediction of financially sound defaults. The loss of Type I errors is significantly larger than that of Type II errors. The power of these empirical models lies in the indicators that reflect capital adequacy, operating efficiency and liquidity. The most significant ratios are those of interest rate spread and working capital to total assets.

**Practical Implications –** Supervisory authorities aim at minimizing the Type I error rate and calibrating models to carry a low Type I error. The proposed integrated model demonstrates superior results reducing Type I errors. Supervisory and regulatory bodies can use the proposed integrated model as a reliable tool for the reduction of bank financial unsoundness to act upon potential failures.

**Originality/Value –** This chapter reveals that the integrated model can be used as a promising technique for evaluating financial unsoundness in terms of its predictive accuracy and

robustness. This model was developed following studies by Canbas, Cabuk, and Kilic (2005), Pasiouras and Zopounidis (2010), Othman (2013) and Mitchell (2015).

**Importance –** This chapter improved the predictability of the MDA, logit and probit models by combining these models. New cutoff points increased the predictive accuracy of the models and integrated model reduced Type I errors.

## 5.1 Introduction

As mentioned in Chapter 2, low asset quality, high exposure to market risk and inadequate internal monitoring have become the causes of the vulnerability of Kazakhstan banks in recent years. Prediction and monitoring of financially unsound banks is of prime importance in minimizing the cost of bank failure. A system of monitoring and supervising the banking sector requires some statistical methods to predict bank failure as early and accurately as possible in order to be able to act in sufficient time. Prior studies focused on developed countries, in particular the USA. There are few studies on bankruptcy prediction models in developing countries in general and in the post-soviet countries, in particular. The majority of the studies used statistical methods such as MDA, logit and probit. The current study employed statistical models to predict bank unsoundness for a sample of Kazakhstan banks. It also developed an integrated model in order to improve the predictability of bank financial unsoundness.

Chapter 4 demonstrated modest predictive ability of the original and re-estimated Altman models of the Z"- Four-Factor Model for non-manufacturing companies and the EM Score - Four-Factor Model for Emerging Markets to predict the financial unsoundness of Kazakhstan banks.

The current chapter examines MDA, logit and probit statistical models and integrates them to improve the predictive power of the model. In Chapter 3, a structure of the banking sector based on a cluster based methodology for the assessment of the financial soundness of banks has assigned the status of soundness and unsoundness to banks on 1$^{st}$ January, 2014. Six unsound Kazakhstan banks with six matching sound banks were selected as a sample for this study. Sound banks were isolated taking into account their size (total assets), specialization and branch' networks. These 12 banks account for 81.3% of the total assets of the banking sector. Data are collected from the annual financial reports from 1$^{st}$ January, 2008 to 1$^{st}$ January, 2014. 1$^{st}$ January, 2014 was selected as a benchmark year. Sample was divided into two parts: sample A (1$^{st}$ January, 2008 to 1$^{st}$ January, 2012) was used for model construction; sample B– (1$^{st}$ January, 2013 to 1$^{st}$ January, 2014) was used for model quality assessment.

The signaling ability of the MDA, logit and probit models in predicting the financial of banks unsoundness was tested. These models identified major signals of unsoundness in capital adequacy, management, earnings and liquidity. The predictability of bank failure using these models was improved using: the calibration of the cutoff points by percentile and the combination of all three models into one integrated prediction model. All constructed models had a high predictive ability. The Integrated model minimized Type I errors and demonstrated superior results.

The second section of this chapter discusses key related prior studies on prediction models of bank bankruptcy. This is followed by the research methodology which describes the research design and process. Then the empirical results of the MDA, logit and probit models are presented. The integrated model is tested in the next section to improve the predictability of the model and reduce the errors. Finally, the chapter is concluded with comparative analyses of four the empirical models by their predictive performance: using percentage of Type I errors, percentage of Type II errors, predictive ability of the model and prediction accuracy in the time horizon.

### 5.2 Literature Review

The 2008 financial crisis and its consequences have created massive cost for the economies of all countries of the world. The systems of early crisis warning in the banking sector did not seem to work effectively. The recent financial crisis highlights the needs for improved tools to identify troubled banks on a more timely basis (Kerstein and Kozberg, 2013). The number of prior studies on the prediction of bank failure is enormous. To develop a statistical prediction model, it is necessary to study the academic research and the practice of bankruptcy prediction.

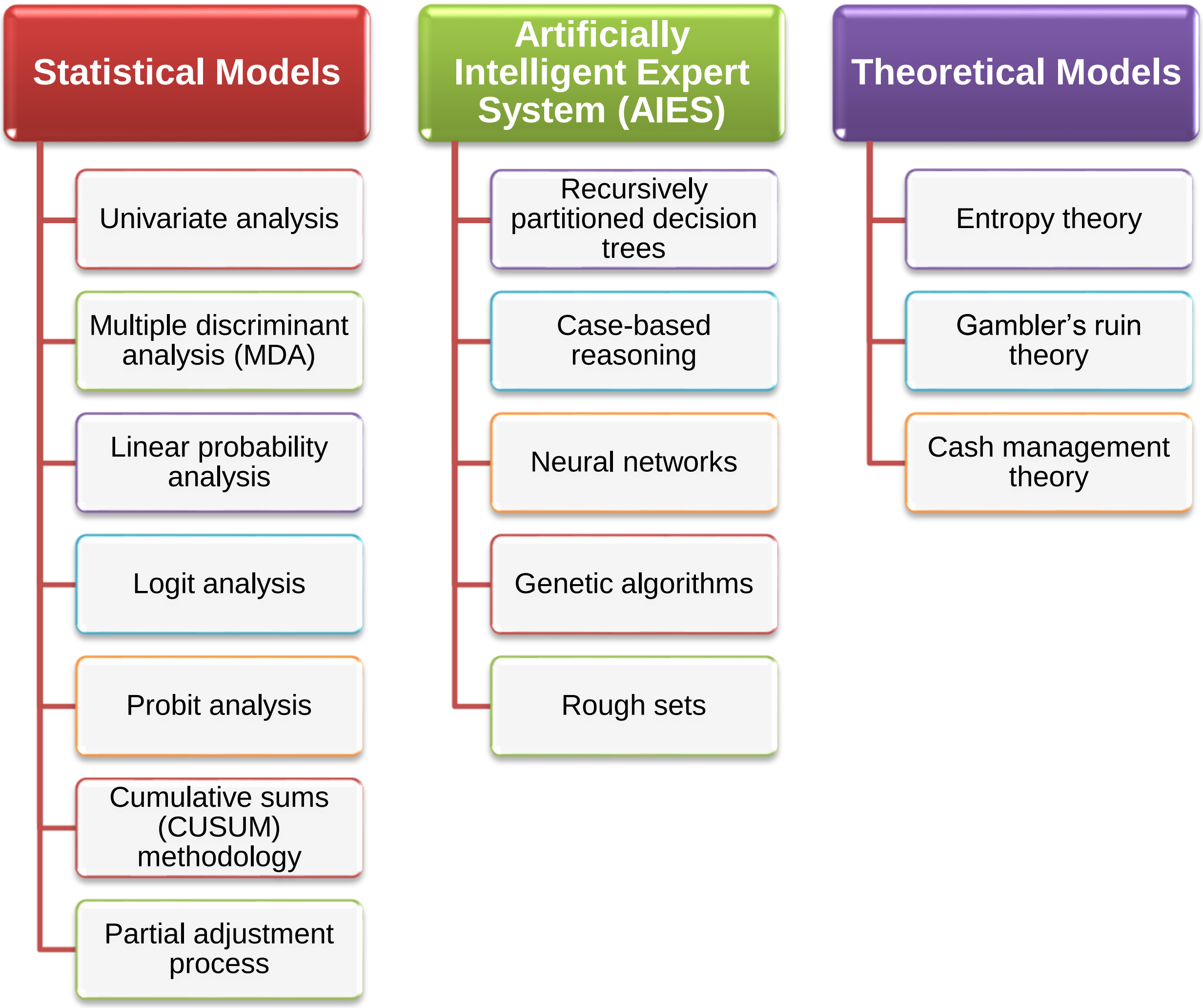
This section discusses the bankruptcy prediction models. It starts with the pioneer studies of Beaver (1966), Altman (1968), Ohlson (1980) and Zmijewski (1984) who proposed to use MDA, logit and probit analysis in failure prediction models. Further, the strengths and weaknesses of MDA, logit and probit models were discussed. Also, key prior studies on bank bankruptcy prediction were reviewed by the proposed models, countries and samples.

The first studies of the analytical coefficients for predicting possible difficulties in the financial performance of companies were carried out in the United States in the early 1930s (Horrigan, 1968). Beaver (1966) and Altman (1968) were the first to employ financial ratios and advanced statistical techniques to predict bank failure. Since that time this approach has become very popular.

Statistical models to predict the future status of bank were developed in the 1990s. These models focus on the use of an early warning system. The impetus for the study of such models was the wave of bank defaults in the United States in the early 1990s. The models used modern statistical and econometric techniques and are based on actual data. The United States, in the only country which the statistical (econometric) models are used in practice by the two regulatory bodiesof the Federal Reserve and the Federal Deposit Insurance Corporation (FDIC). These models are known as SEER (System for Estimating Examination Ratings) and SCOR (Statistical CAMELS Off-site Rating).

Aziz and Dar (2004) classify bankruptcy forecasting models into: Statistical models, Artificially Intelligent Expert System (AIES) models and Theoretical models (Figure 5.1).

**Figure 5.1: Models of Identification of Potential Bank Failure**




**Source:** Aziz and Dar (2004)

Aziz and Dar (2004) provide a critical analysis of the most frequently used bankruptcy forecasting models and compare them in terms of their predictive powers. They concluded that, in effect, these models are not much different from each other and, historically, researchers first suggested the use of statistical models. Recently, academics were motivated to invent technology-oriented models such as Artificially Intelligent Expert System (AIES) models. They could be considered as a sophisticated automated outgrowth of the statistical approach. However, statistical models still play an important role in predicting bank failure.

Apart from the historically most common statistical models, there are also some specific models, drawn from a wide universe of science that can be used for predicting the bankruptcy of banks. The latter relate to different areas from machine learning to genetics.

Change in the perception of machines as being able to learn in a similar way to human beings, gave rise to the new forms of problem solving models:

Artificial Intelligent Expert Systems:

Recursively Partitioned Decision Trees is a form of inductive learning, which works by continuously splitting any given task by a decision tree into several sub-categories, that become more and more identical, until some final condition is met (Pompe and Feelders,1997). For bankruptcy prediction, the final nodes of the tree should be either "bankrupt" or "healthy". The positioning of the company on a tree indicates the group in to which it falls and its probability. The main disadvantage is the need for a recurring review of already analysed variables.

Case Based Reasoning is a method that uses previous similar cases in order to find the solution to the current case. It operates in stages by, firstly, extracting the problem. Then after selecting the related cases from the pool of the existing examples, it uses them to fit into the given problem in order to arrive at a solution. Finally this solution will be saved and stored as a new case. The only problem with this method is the fact that it is still at an early stage of development, thus giving potential for significant improvements (Aziz and Dar, 2004).

Neural Networks use the same principle as the human brain, basing decisions on the signals received from the nerves (nodes - in case of the computers), with appropriate weightings given to different interconnections. For bankruptcy particularly, information is gathered from the signals to calculate the probability of a firm becoming bankrupt. The main problem of using such model lies in the large amount of time required to set up and test the system.

Genetic Algorithms operate by searching for the solutions from the total population represented by a binary code (0 and 1). Then the superior solutions are chosen and the process is run until all the outcomes are homogeneous to a required degree. In case of bankruptcy, cut-off points are used. However, as outlined by Aickelin and Dowsland (2003), there is no common way of inputting constrains into these algorithms.

Rough sets models are based on a classification of the information into categories. These are then translated into information tables to determine the decision rules by inductive reasoning. The same principles apply to forecasting bankruptcy where a model classifies a given company into a "bankrupt" or "healthy" category, basing the classification rules on the information tables. The danger comes from the fact that such models are not efficient in working with numerical data due to "multimodality and high noise sensitivity" (Yasdi, 1995).

Unlike AIES models, theoretical models look into the causes of the bankruptcy and the ways of using them to predetermine the probability of a firm becoming bankrupt in the future.

The Balance Sheet Decomposition measure looks at the changes within the balance sheet and the company's ability to remain in equilibrium. Fluctuations are seen as a negative sign, indicating the possibility of future problems. However, this gives rise to a major critique, as the model fails to differentiate positive from negative changes.

Gambler Ruin Theory suggests that a gambler would play until he loses all his money. When a firm is perceived as a gambler, bankruptcy is the final stage and cash flows rise and fall at any other point in time. The major flaw of the model is in the fact that it does not consider the firm's ability to borrow external capital to cover the losses.

Cash management theory suggests that negative cash flow outweighing positive cash flow over a period of time may cause a firm to become bankrupt. However it fails to recognize any other factors of potential influence.

Sahajwala and Van Den Bergh (2000) noted two essential features of statistical models. First, statistical models attempt to identify high-risk banks in advance of failure. Second, appropriate statistical models can determine causal economic relationships between explanatory variables and outcomes such as bank fragility, distress and failure using quantitative techniques.

Aziz and Dar (2004) noted that more than 30% of bankruptcy prediction studies use MDA model, while another 21% apply the logit model. Both models make up 77% of the statistical models group. This fact suggests that other types of statistical models failed to have adequate attention from researchers. Logit and probit analysis belong to the same family of binary choice statistical models but the probit model is less commonly used. The major difference between these two models is in function distribution. It is logistic in the case of the logit model and normal in the case of the probit model. The logit model is more attractive because it is similar to the cumulative normal function but uses easier calculations. There is always a unique maximum for the logit model and almost all non-linear procedures will find the estimated options (Hryckiewicz, 2010). Also, Du Jardin (2009) analyzed 190 journal papers on bankruptcy prediction models and detected that roughly 50 studies (26%) use discriminant analysis, 40 (21%) use logistic regression and 75 (39%) use neural networks.

AIES and theoretical models, also called structural models, are superior predictors of default (Mitchell, 2015). The efficiency of structural models is explained by use of market information. Market variables reflect all the information from accounting reports and also contain additional data. Since they are not influenced by the accounting policies of the banks, they are less subject to managers' manipulation, which makes them less biased and more applicable for prediction purposes. The output of the structural models is not dependent on time or sample (Agarwal and Taffer, 2008). However, Reisz and Perlich (2007) noted that accounting based models' predictability is better within a one-year horizon, whilst structural models outperform them on longer 3-10 years periods.

All theoretical models are based on a number of assumptions, like the normality of stock returns and zero-coupon debt (Saunders and Allen, 2002) which therefore undermines their applicability in real world. Also, structural models are limited to using developing countries due to the lack of market information. Therefore it is arguable that theoretical models' outperform their comparators not because of their superior predictive abilities (Hillegeist et al., 2004), but due to the poorer results of the latter.

At the same time, Bell (1997) noticed that bank regulators use simple linear processes when making decisions about closure of commercial banks. Attempts to model nonlinearities and interactions through multiple connections within a neural net framework failed to produce a dominant predictive model. That is why it is not necessary to use complex nonlinear decision making models. The argument was supported by Aziz and Dar (2004) that the superiority of AIES including neural networks becomes questionable regarding the predictive powers of individual models. In this context, MDA and logit models provide consistently superior predictive accuracies and reported low average Type I & II error rates.

Finally, Kimmel (2016) concluded that researchers use such statistical methods as MDA, logit and probit because they are proven and widely accepted, while newer, more complex models are still under development and no clear consensus exists as to the version or implementation which is superior. However, most prior studies have been conducted in developed countries as shown in Table 5.1. Thus there is a lack of evidence about the effectiveness of these models in predicting bank financial unsoundness in developing countries. Therefore, the current study examines the ability of three statistical models to predict bank financial unsoundness in the developing country of Kazakhstan.

Prior studies use statistical techniques such as multiple discriminant, logit and probit analysis to predict bankruptcy. These methods have been developed by various authors and presented over the last five decades starting from Beaver (1966). The most well-known studies are there by Altman (1968) – MDA model; Ohlson (1980) – logit model and Zmijewski (1984) – probit model. All used accounting ratios. The well-known financial analyst Beaver (1966) has proposed a system of defining the probability of bankruptcy of 79 failed and 79 non-failed firms in 38 industries. His five-factor model includes financial indicators. Beaver was the pioneer in constructing a corporate failure prediction model. He was the first who used accounting ratios when applying the univariate discriminant analysis model. His model encouraged the development of a multivariate analysis by Altman (1968).

**Altman's Z-score Model** was first published in 1968. He employed multiple discriminant analysis (MDA) for the first time using financial ratios to predict future bankruptcy. It was described in detail in Chapter 4. Aziz and Dar (2004) noted that MDA is the most popular method of bankruptcy prediction.

Ohlson's model (1980) is the next of the most commonly used insolvency forecasting models using logit analysis. Logit model measures the relationship between one dependent variable and one or more independent variables using a logistic function for estimating probabilities. For the prediction of bankruptcy logit analysis has advantages over discriminant analysis. Thus, one of the necessary conditions of a discriminant model is the normal distribution of the discriminant variables. Practice shows that normal distribution often is not observed where the logit model requires logistic distribution which has heavier tails than normal distribution.

Zmijewski (1984) is one of the first who has employed probit analysis to predict bankruptcy of firms listed on the New York Stock Exchange during the period 1972 through 1978. The model used only three indicators. However the probit analysis like the MDA requires a normal distribution of the data.

Khermkhan et al. (2015) compared the forecasting efficiency of three statistical models. They found that the logit and probit models are flexible and easy to understand and explain. MDA also is an appropriate tool but requires more complex techniques to identify several multivariate groups.

**Table 5.1: Comparison of MDA, Logit and Probit Models**

| | MDA | Logit | Probit |
|---|---|---|---|
| ß | Coefficient | Probability | Probability |
| Complexity | Low | Very Low | Low |
| Elasticity | Low | High | High |
| Accuracy | Sound | Sound | Sound |
| Works well with | Linear regression, Multivariate | Linear regression | Linear regression |
| Advantages | 1. Can explain complex multivariate.<br>2.Provides sound prediction when the relation of variables is linear | 1. Convenient and easy to understand.<br>2. Can explain the variable as simple equations.<br>3.Provides sound prediction when the relation of variables is linear | 1. Convenient and easy to understand.<br>2. Can explain the variable as simple equations.<br>3.Provides sound prediction when the relation of variables is linear |
| Disadvantages | Limited to linear equations | Limited to linear equations | Limited to linear equations |

**Source:** Khermkhan et al. (2015)

Indeed, these classical bankruptcy prediction models have given rise to an extensive body of literature. The MDA, logit and probit models formed the basis for the vast majority of the studies on bank bankruptcy prediction, designed prediction rules and assessed the determinants of financial failure.

The authors mentioned above are widely cited by academicis who studied bankruptcy prediction for both companies and banks. Ohlson (1980) and Zmijewski (1984) were considered as the first researchers who used logit and probit analysis. However, Martin (1977) and Bovenzi (1983) were the first who applied logit and probit models to predict bank failure. Obviously the number of studies on bank failure is significantly less than on company bankruptcy and hence they are cited less frequently.

A summary of prior empirical studies that have employed the MDA, logit and probit models to predict bank failure is provided in Table 5.2.

**Table 5.2: Summary of Prior Studies on Bank Bankruptcy/Failure Prediction**

| Article | Method | Country | Sample | Status | Predictive ability, % | Type I, % | Type II, % |
|---|---|---|---|---|---|---|---|
| Meyer and Pifer (1970) | MDA | USA | 39 solvent and 39 closed insured banks<br>Period: 1948 - 1965 | Bankrupt and solvent banks (closed insured bank) | 80.00 | 3 | 0 |
| Sinkey (1975) | MDA | USA | 110 problem banks and 110 non-problem banks<br>Period: 1969-1972 | Problem, non problem | 77.67 | 13.59 | 22.3 |
| Martin (1977) | Logit regression | USA | 5,598 observations, 23 cases of default<br>Period: 1970-1976 | Failed and non-failed banks. | 82.00 | n/a | n/a |
| Bovenzi (1983) | Probit analysis | USA | 72 failed and 150 non-failed<br>Period: 1977-1981 | Failed are commercial banks that required outlays from the Deposit Insurance Fund | 91.00 | n/a | n/a |
| Article | Method | Country | Sample | Status | Predictive ability, % | Type I, % | Type II, % |
| West (1985) | Logit analysis, Factor analysis | USA | 125 problem and 1300 sound banks<br>Period: 1980-1982 | Sound and Problem banks according to the CAMELS rating system. Rating 1,2 – sound, 3-5 – problem. | 90.5o | n/a | n/a |

**Source:** Author

Continuation of Table 5.2

| Article | Method | Country | Sample | Status | Predictive ability, % | Type I, % | Type II, % |
|---|---|---|---|---|---|---|---|
| Espahbodi (1991) | Logit analysis | USA | 48 failed and 48 non-failed US banks Period: 1983. | Failed and non-failed banks | 86.3o | n/a | n/a |
| | Discriminant models | | | | 84.24 | n/a | n/a |
| Estrella, Park and Perisitiani (2000) | Logit regression | USA | 634 failure and 61370 non failure (observations) Period: 1989-1993. | Failed and non failed thrift institutions | 80.00 | 4.8 | 7.3 |
| Kuznetsov (2003) | Logit model | Russia | 261 failed and 1308 non- failed Period: 1996 to 2001 | Failed and non failed | 87.00 | 68.2 | 2.6 |
| Rahman et.al (2004) | Logit model | Indonesia, South Korea and Thailand | Non problem banks in Indonesia, South Korea and Thailand are 30, 29 and 17 respectively. The problem banks for Indonesia, South Korea and Thailand are considered as 19, 21 and 12 respectively. Period: 1995-1997 | Financial distress | 85.00 | 11 | 20 |
| Canbas, Cabuk and Kilic (2005) | MDA, Logit and Probit analysi, PCA and IEWS | Turkey | 18 failed and 22 non-failed privately owned commercial banks Period: 1994-2001 | Failed and non-failed | from 87.50 to 90.00 | from 15 to 25 | from 5 to 30 |
| Ioannidis, Pasiouras and Zopounidis (2010) | MDA, UTADIS, ANN, k-NN, OLR and Stacked model | 78 countries | 944 banks at the end of 2007 or March 2008 | Very strong or strong banks; adequate banks, banks with weaknesses or serious problems | from 68.00 to 95.00 | n/a | n/a |

**Source:** Author

Continuation of Table 5.2

| Article | Method | Country | Sample | Status | Predictive ability, % | Type I, % | Type II, % |
|---|---|---|---|---|---|---|---|
| Othman (2013) | MDA, Logit analysis, Probit analysis Factor analysis and Integrated model | Malaysia | 10 Malaysian Islamic banks Period: December 2005 to September 2010 | Financial distress | from 73.00-93.00 | n/a | n/a |
| Betz et. al (2014) | Logit model | Europe | 546 banks from 2000 to 2013 | Vulnerabilities leading to distress | from 57.00 to 60.00 | n/a | n/a |
| Mitchell (2015) | Logit model, PCA, Combination model | USA | 519 defaulted banks years and 5,965 non defaulted banks years from 1995 to 2012 | defaulted and non defaulted bank | 82.40 | 9.22 | 18.3 |
| Affes and Hentati-Caffel (2016) | Logit | USA | 410 failed banks, 5805 non-failed banks from 2008 to 2013 | Failed and non-failed | 98.82 | 33.33 | 0.6 |
| | Canonical discriminant analysis | | | | 98.59 | 46.67 | 0.6 |
| Kimmel, Thornton Jr. and Bennett (2016) | Logit, MDA, PHM, Trait and LOESS | USA | FDIC bank failures 1986 through June 2010 focused on 3 publicly traded commercial banks | Bank failures | 96.00 | n/a | n/a |

**Source:** Author

As can be seen from Table 5.2 the authors classified banks as bankrupt/non-bankrupt, failure/non-failure, problem/non-problem, troubled/non-troubled, distressed/distressed, sound/problem, bankrupt/solvent, default/operating, financial distress. The sample of banks varies from 10 to 2506.

Observed studies used a single prediction model (42%) and two or more models (52%). They employed statistical models such as the MDA model (42%), the logit model (79%), the probit model (42%) and they proposed integrated models (21%) to improve the classification accuracy of individual prediction models.

Most of the studies are conducted in developed countries, in particular the USA: Meyer and Pifer (1970), Sinkey (1975), Martin (1977), Bovenzi (1983), West (1985), Espahbodi (1991),Thomson (1991), Bell (1997), Estrella, Park and Perisitiani (2000), Catanach and Perry (2001), Mitchell (2015), Affes and Hentati-Caffel (2016), Kimmel, Thornton Jr. and Bennett (2016) and Betz et. al (2014) in Europe. There are farfewer studies on developing countries, for example, Rahman et.al (2004), Canbas, Cabuk and Kilic (2005), Ioannidis, Pasiouras and Zopounidis (2010),Othman (2013). Kuznetsov (2003) used the logit model to predict default of Russian banks as a case of country of transition.

This study employs MDA model following to Meyer and Pifer (1970), Sinkey (1975), Martin (1977), Canbas, Cabuk and Kilic (2005), Ioannidis, Pasiouras and Zopounidis (2010),Othman (2013) Kimmel, Thornton Jr. and Bennett (2016); Logit model like Martin (1977), West (1985), Espahbodi (1991), Thomson (1991), Bell (1997), Estrella, Park and Perisitiani (2000), Catanach and Perry (2001), Kuznetsov (2003), , Rahman et.al (2004), Canbas, Cabuk and Kilic (2005), Ioannidis, Pasiouras and Zopounidis (2010),Othman (2013), Betz et al (2014), Mitchell (2015), Affes and Hentati-Caffel (2016), Kimmel, Thornton Jr. and Bennett (2016); Probit model like Bovenzi (1983), Canbas, Cabuk and Kilic (2005), Othman (2013) to predict bank unsoundness using accounting variables for the Kazakhstan banks.

Also current research develops an integrated model following to Canbas, Cabuk and Kilic (2005), Ioannidis, Pasiouras and Zopounidis (2010), Othman (2013), Mitchell (2015) in order to improve the predictability of bank financial unsoundness.

The authors' studies indicated in the Table 5.2 are discussed in detail below. These studies cover a publication period of 1970 to 2016. Despite dedicated effort over more than four decades, academics still tend to disagree over the particular models which are more reliable, useful and have higher prediction accuracy for the case of bank unsoundness prediction. Meyer and Pifer (1970) and Sinkey (1975) were the pioneers in bank bankruptcy prediction models. They followed Altman and used MDA analysis for US bank bankruptcy prediction. Meyer and Pifer (1970) investigated the causes of US bank failures and concluded that bankruptcy resulted from financial irregularities. They developed an MDA model based on the data of 39 of the 55 commercial banks that were closed in USA between 1948 and 1965. The main criteria for selecting these banks are the availability of information for the six years preceding the bankruptcy. The financial variables that could potentially lead to insolvency have been defined by using a multivariate statistical method. The predicting accuracy is 80% for one or two years before failure. They calculated the percentage of errors in classifying the original sample by type of error at alternative cut-off levels. The regression equations were analysed up to one and two reporting periods prior to failure using five cut-off values of 0.3, 0.4, 0.5, 0.6 and 0.7 and a different number of variables of 5, 6, 7, 8 and 9. Meyer and Piefer argued that the four groups of factors that influence bank failure are: local economic conditions, general economic conditions, quality of management and integrity of employees. According to them, they cannot estimate local economic conditions and general economic conditions.

Sinkey (1975) classifies US banks as problem and non-problem using the method of discriminant analysis (MDA). The study is based on data from the balance sheet and income statements. The empirical findings have shown that bank indicators such as asset composition, terms of loan agreements, capital adequacy, sources and use of income, efficiency and profitability are reliable discriminators between the groups of troubled and non-troubled banks. Both studies achieved high predictive ability and a relatively low rate of Type I and Type II errors.

Later in 1977, Martin first applied a binary choice model and then West (1985), Estrella, Park and Perisitiani (2000) used logit analysis for the prediction of bank default. Martin (1977) has analyzed 5,598 observations of which only 23 are cases of default. The work has been carried out on the data of banks in the USA and the model forecasting horizon is 1-2 years. The predictive ability of the model accounts for 87% of the correct classification of bankrupt banks and 88.6% of the correct classification of non-bankrupt banks. In general, the degree of accuracy is similar to that of the Altman model (1968). The explanatory variables are grouped into four main categories of asset risk, liquidity, capital adequacy, and income.

West (1985), in addition to logit analysis, also uses factor analysis to measure the condition of individual banks with a view to their classification as troubled and non-troubled. The model employs financial ratios and information from the US Federal Financial Institutions Examination Council data. 1,900 of 2,900 US banks have been selected for the research. The components identified in the factor analysis are closely related to the CAMELS components of capital adequacy, asset quality, management, earnings, and liquidity. The obtained factors are further used in logit analysis as variables for the differentiation between troubled and non-troubled banks. Banks are grouped into troubled and non-troubled categories according to the CAMELS rating system. Banks with scores of 1 and 2 are considered stable and are considered troubled with scores of 3, 4 and 5. The results of empirical research show that the combination of factor analysis with logit analysis is a promising tool for an early warning system.

Estrella, Park and Perisitiani (2000) also used a logit model. They discussed and compared the effectiveness of different coefficients in predicting US bank failure. They suggest that simple coefficients such as leverage or capital to gross revenue predict bank failure as effectively as more sophisticated risk-weighted ratios in the time horizon of one or two years. However, the purpose of their work was not to deny the need for the publication of complex ratios of capital adequacy but to show that simple ratios can be very informative. To assess the predictive ability of the indicators they used logit regression. Logit models proved their superiority in predictive ability.

Bovenzi et al (1983) started a series of studies on the development of bankruptcy forecasting models using probit analysis. Prediction of US bank failure is based on the data from the US

Federal Financial Institutions Examination Council “Call Reports” for the period from 1977 to 1983 (Based on the FDIC documents). The prediction is made for two or three years prior to the failure. Three models developed by Bovenzi et al. (1983) are crosschecked with the CAMELS rating data. Models based on ratios predict bank failure more effectively than models based on the CAMELS rating.

Authors have employed different statistical techniques together to compare their performance. Espahbodi (1991), Mitchell (2015), Affes and Hentati-Caffel (2016) and Kimmel, Thornton Jr. and Bennett (2016) investigating bank failure in USA used two or more models. Espahbodi (1991) tested and compared the predictive ability of models based on logit and discriminant analysis distinguishing between failed and non-failed banks. The study was based on 48 US banks that failed in 1983 matched with another 48 non-failed banks according to the geographical location and size. During the study due to a lack of information the number of banks in the sample had dropped to 37 failed and 33 non-failed banks. The accuracy of the logit model was 87.67% for failed banks and 77.71% for non-failed banks and that of discriminant analysis was 86.3% and 84.28% respectively. This study had shown that the logit model gives a more accurate prediction of bank failure than the discriminant model.

Mitchell (2015) compared the performance of structural and accounting models. The main argument against the accounting model was the multicollinearity problem and the researcher suggested the use of PCA analysis to improve the model. The study compared the logit and Merton default models and then evaluated a combined model. The accounting model outperformed the structural model but a combination of both models performed more accurately than the accounting model.

Kimmel, Thornton Jr. and Bennett (2016) investigated whether statistical early warning systems (EWS) can inform markets about problematic banks. They utilized five “archetypical” EWS using a unique dataset from 1986 through to 2009. They found that LOESS and MDA models are clearly superior although logit, PHM, and trait analysis also perform well.

The studies mentioned above studies investigated bank failure prediction in the USA. Betz et.al's (2014) study focused on European countries and developed an early-warning model for predicting vulnerabilities leading to distress in banks. This study calibrated the early-warning model to take into account the potential systemic relevance of each individual financial institution. The results of the evaluation framework conclude that a policymaker might be more concerned with avoiding bank distress than issuing false alarms. When bank is predicted to be in distress this triggers an internal in-depth review of the fundamental measures, the business model and peer performance. If the analysis reveals that the signal is false, there is no loss of credibility as the model results are not published. Also they mentioned the importance of large banks for policymakers concerned with systemic risk.

The other reviewed studies considered bank failure in developing countries. For example, Kuznetsov (2003) and Rahman (2004) used the logit model as the first author to predict default of Russian banks and the financial distress of Indonesian, South Korean and Thailand banks. Kuznetsov (2013) in his study examined the impact of the crisis of 1998 on the Russian banking system. This analysis focused on the factors that have conditioned the successful overcoming of the crisis. For this purpose bank balance sheet data on the eve of the crisis were analyzed using econometric methods (logit analysis). Special attention was given to the impact of public debt and loans to the real sector of the economy in the balance sheet. Some of the key characteristics of bank reliability appeared insignificant and it was concluded that not only strong banks but also some inefficient and weak banks had survived the crisis. These banks took advantage of weak legislation, lax supervision and the possibility to use political and administrative resources due to the merger of governmental and banking institutions.

Rahman et.al. (2014) conducted research to identify indicators of distress in Asian countries as an example. The study included the banks of Indonesia, South Korea and Thailand. A logistic regression method was employed using the data for the period from 1995 to 1997. For each country a specific model was developed based on 12 variables selected as the optimum to identify problem banks.

A study by Ioannidis, Pasiouras and Zopounidis (2010) also investigated a sample from several countries and used six quantitative techniques to classify banks in three groups of very strong and strong banks; adequate banks; and banks with weaknesses or serious problems. They compared the models developed with financial variables only with models that incorporate regulatory, institutional and macroeconomic variables. Models with only financial variables have weak prediction accuracy. The country-level variables substantially improved the accuracy. The highest accuracy was shown by models with multi-criteria decision aid and artificial neural networks. Also they developed stacked models that combine the predictions of the individual models at a higher level. The stacked models outperformed the corresponding individual models but they found no evidence that the superior stacked model can outperform the superior individual model.

While Ioannidis, Pasiouras and Zopounidis (2010) developed a stacked model on a cross-country level, studies by Canbas, Cabuk, and Kilic (2005) and Othman (2013) proposed integrated models on a sample of Turkish and Malaysian banks respectively. Canbas, Cabuk, and Kilic (2005) used four well known statistical techniques. Principal component analysis was used to explore the basic financial characteristics of the banks. On the basis of these characteristics, discriminant, logit and probit models were obtained. IEWS was effectively employed in bank supervision and could help to avoid bank restructuring costs.

Othman (2013) has conducted research using data from 10 Islamic banks in Malaysia. For these banks models for forecasting bankruptcy probability have been developed using MDA, logit and probit analyses and they demonstrate high predictive ability. The data for the analysis were the coefficients generated based on the financial statements which were previously grouped into principal components by means of factor analysis. The discriminant analysis and the logit model classify banks with an accuracy of 70% and the probit model with 60%. Also, Othman used the combination of principal component analysis and the three parametric models (discriminant, logit and probit) and constructed an integrated model for bank distress prediction.

### 5.3 Research Methodology

This study utilizes statistical models to predict bank financial unsoundness, using: MDA, logit and probit analyses. It employs a set of indicators selected and analysed in Chapter 3. It seeks to answer the following research question:

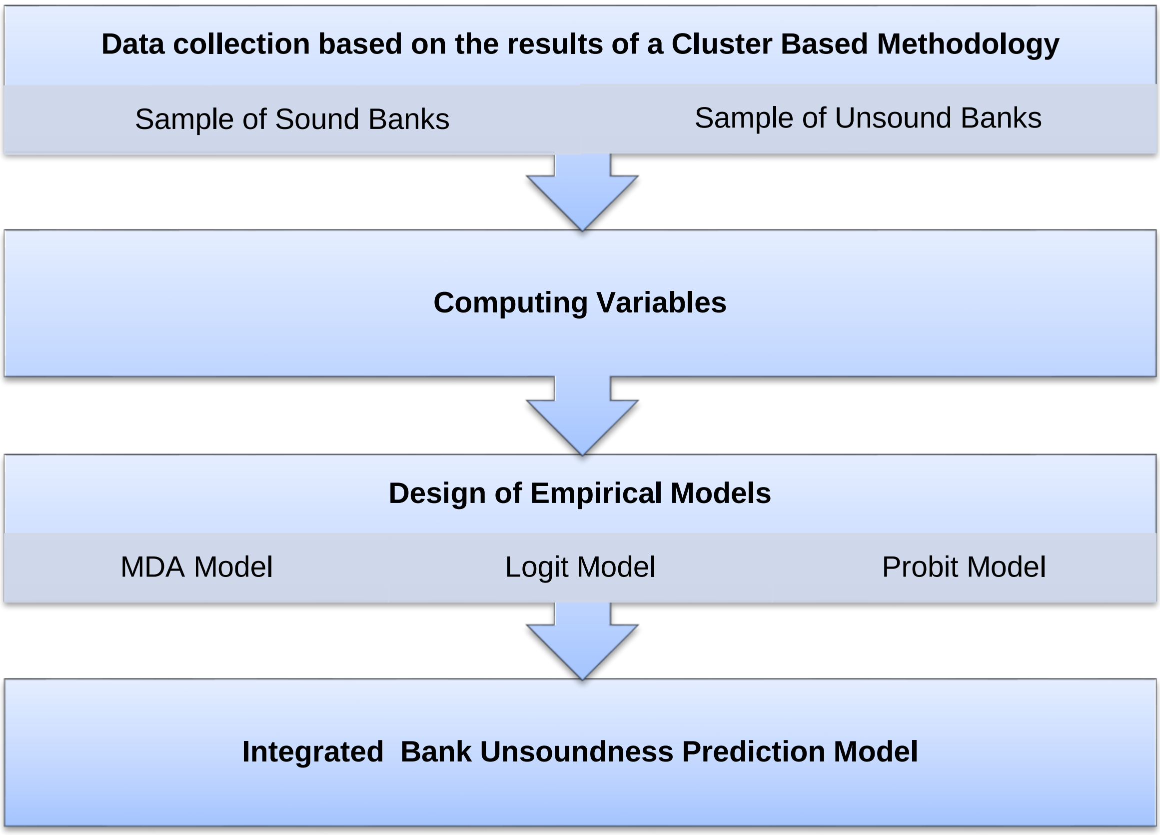
Can the predictability of bank financial unsoundness be improved by using statistical models such as MDA, Logit and Probit?

To achieve this goal the predictability of these models is investigated and then an integrated model using MDA, logit and probit analysis is developed.

#### 5.3.1 Research Process

This chapter utilises the financial ratios and the classification into sound and unsound banks obtained in Chapter 3. The process of developing the integrated model is presented in Figure 5.2.

**Figure 5.2: Process and Design of Integrated Prediction Model of Bank Unsoundness**




**Source:** Author

The process starts from the data collection. In Chapter 3, the structure of the banking sector was obtained. A status of sound and unsound banks were assigned according to a cluster based methodology. First, the selected sample is composed of 12 banks of 6 sound and 6 unsound and the share of their assets in the total assets of the banking sector is 81.3% (Table 4.4). The individual banks of each group have been carefully matched taking into account their total assets (size), specializations and branches' networks. This sample was divided into in-sample and out-sample. First group was used for the models design, second for checking the abiblity of models to predict financial unsoundness

The MDA, logit and probit models are employed on the sample of 12 Kazakhstan banks annually in the period from 1$^{st}$ January, 2008 to 1$^{st}$ January, 2014. Since sound and unsound groups of banks were defined on 1$^{st}$ January, 2014, this date is the benchmark. The in- sample consists from observations between 2008 and 2012 years, out sample is 2013 and 2014 years. A set of fifteen financial ratios used in Chapter 3 were computed annually for the period from 1$^{st}$ January, 2008 to 1$^{st}$ January, 2014 (Appendix 5A, 5B).

**MDA analysis** based on certain features (independent variables) assign the object to one of two (or a few) pre-set groups. Such setting of the problem, especially in the case of two predefined groups, very strongly resembles the problem statement for the logistic regression method. The kernel of discriminant analysis is the building of the so-called discriminant function.

$$D = \beta_1 X_1 + \beta_2 X_2 + \ldots + B_n X_n + \alpha, \qquad (5.1)$$

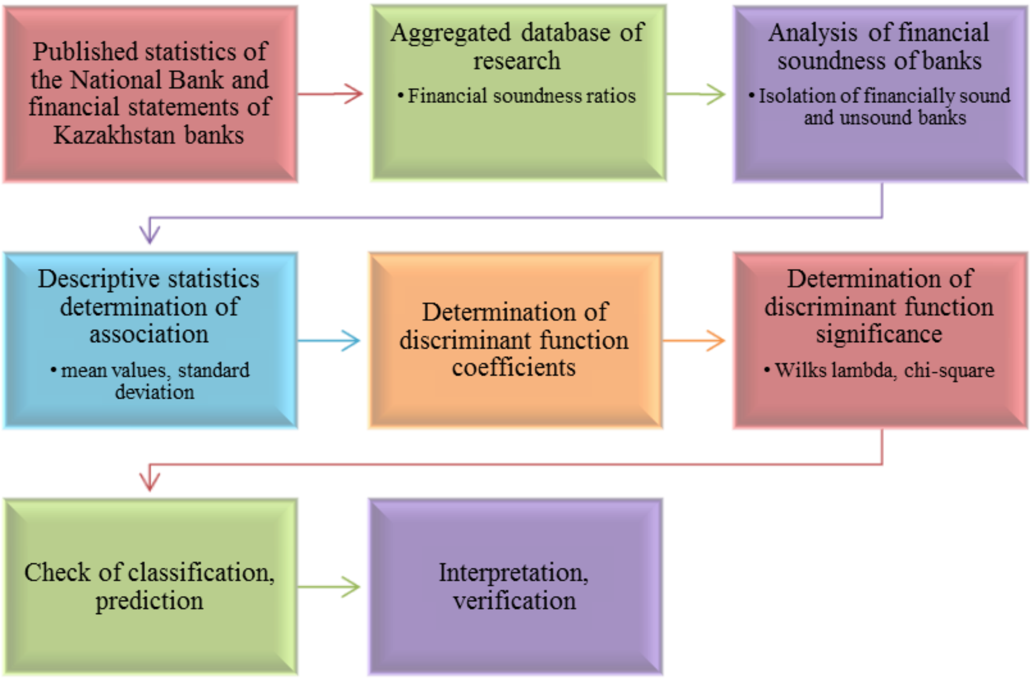
where

D – the discriminant value;
$X_1$ and $X_n$ — the values of variables relevant to the cases under consideration;
$\beta_1 - \beta_n$ — the coefficients to be assessed using the discriminant analysis; and
$\alpha$ – the constant.

The purpose is to determine such coefficients which would make it possible to conduct the partitioning into groups with maximum accuracy based on the discriminant function values.

Discriminant analysis consists of the stages of problem formulation, calculation of discriminant function coefficients, definition of significance, interpretation and validation (Nasledov A., 2013). This process is schematically shown in Figure 5.3.

**Figure 5.3: Algorithm for Building a Model for Prediction of Loss of Financial Soundness of a Bank by Discriminant Analysis (MDA)**




**Source:** Nasledov (2013)

**The logit model** is used to predict the probability of an event by fitting the data to a logistic curve. Using the binary logistic regression the researcher can explore the dependence of dichotomous variables on the independent variables that have any scale.

Commonly a dichotomous variable refers to an event that may or may not occur; the binary logistic regression, in such a case, estimates the probability of the event occurrence based on the values of independent variables.

The probability of event occurrence for some cases shall be calculated by the formula

$$p = \frac{1}{1+e^{-z}} \tag{5.2}$$

where

$$z = \beta_1 X_1 + \beta_2 X_2 + \ldots + B_n X_n + \alpha, \tag{5.3}$$

where

$X_1$ and $X_n$ — the values of variables relevant to the cases under consideration
$\beta_1 - \beta_n$ — the factors to evaluate and
$\alpha$ – error term (the probability of Type I error occurs).

The advantage of using logit models is that there are no problems with the interpretation of the resulting indicator (R), which takes on values only in the range from 0 to 1 and determines the nominal value of probability of entity insolvency. In logit models, such zones are absent because, if the estimated probability (R) is more than 0.5, it is predicted that the event will occur and, if less than or equal to 0.5, the event will not occur.

For calculation of factors of the model, one uses the methods of Inclusion: Likelihood Ratios (LR) and Exclusion: Likelihood Ratios, which are stepwise. Quality assessment of the model is made by calculating multiple indicators. Log Likelihood value describes the model and shows how well it matches the original data. Cox and Snell's R square and Nagelkerke’s R square are the approximations of the values of R- square showing the share of influence of all predictors of the model on the variance of the dependent variable.

**The probit model** is a statistical non-linear model used in various areas and a method of analysis of the dependence of qualitative variables on a set of factors based on normal distribution. In econometrics, probit models are used in the models of binary or multiple choice between different alternatives to model default rates of companies.

The term "probit" is derived from the English “probability unit” and was offered by Chester Ittner Bliss [1899—1979]. The probit model allows one to estimate the probability that the analysed (dependent) variable takes the value 1 at pre-set values of factors (an estimation of share of "units" at a given value of factors). In the probit model, the probit function is modelled as a linear combination of factors including a constant.

In the probit analysis, the probability of banks falling in to one of the two groups is presented as a function of normal distribution

$$P_{pa} = \int_{-\infty}^{Z_{pa}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z}{2}} dz \ , \qquad (5.4)$$

where Zpa equation takes the following form:

$$Z_{pa} = \beta_1 X_1 + \beta_2 X_2 + ... + B_n X_n + \alpha, \qquad (5.5)$$

where

$X_1$ and $X_n$ — the values of variables relevant to the cases under consideration
$\beta_1 - \beta_n$ — the factors to evaluate and
$\alpha$ – error term.

Logit and probit models are very similar as both are models of binary choice. The difference between the models is in the distribution of error term. If the error term has a standard normal distribution, the probit model should be used, if the error term has a logistic distribution the logit model should be used.

To increase the predictability of MDA, logit and probit models, an approach by Begley et al. (1996) and Wu et al. (2010) was used. The obtained discriminant score and probabilities by logit and probit analysis were ranked from lowest to highest. It was assumed that the superior cut-off point is between 25 and 75 percentiles. The cut-off points were selected as the percentile at which the sum of Types I and II classification errors was minimized and the predictive ability was at highest.

Finally, as a concluding step, a comparison between the outcomes of all empirical models employed in this chapter is developed for the MDA, logit, probit and integrated models. The comparative analysis allowed for four features of the percentage Type I errors; the percentage Type II errors; the predictive ability of the model and the prediction accuracy annually. Type I error represents a misclassification of an unsound bank as sound. Conversely Type II error is a statistical term identified with misclassification by a model when the system wrongly classifies a sound bank as unsound (Sahajwala and Van Den Bergh, 2000).

## 5.4 Empirical Results: MDA Model

### 5.4.1 Analysis of the Independent Variables

The purpose of variables analysis is to identify the variables that could be used to efficiently distinguish sound from unsound banks. Mean values, standard deviations, Wilk's Lambda, T, F and Mann-Whitney U-test of fifteen variables are calculated and presented in Table 5.3.

**Table 5.3: Test of Equality of Group Means 2008 - 2012**

| Variable | Sound banks | | Unsound banks | | Wilks' Lambda | F test (p–value) | T test (p–value) | Mann–Whitney U-test (sig.) |
|---|---|---|---|---|---|---|---|---|
| | Mean | Std. Dev. | Mean | Std. Dev. | | | | |
| R1 | 0.249 | 0.247 | 0.070 | 0.279 | 0.893 | 0.786 (0.261) | 2.632* (0.005) | 410 (0.554) |
| R2 | 0.196 | 0.214 | 0.033 | 0.279 | 0.899 | 0.589 (0.080) | 2.546* (0.007) | 445 (0.941) |
| R3 | 0.240 | 0.247 | 0.074 | 0.195 | 0.875 | 1.597 (0.107) | 2.884* (0.003) | 390.5 (0.379) |
| R4 | 0.909 | 2.060 | 0.122 | 0.192 | 0.930 | 115.61* (0.000) | 2.083* (0.023) | 429 (0.756) |
| R5 | 5.489 | 2.657 | 4.908 | 2.775 | 0.988 | 0.917 (0.408) | 0.828 (0.206) | 339 (0.101) |
| R6 | 0.045 | 0.037 | 0.218 | 0.226 | 0.773 | 0.027* (0.000) | -4.124* (0.000) | 250* (0.003) |
| R7 | 0.222 | 0.192 | 0.905 | 1.482 | 0.902 | 0.017* (0.000) | -2.505* (0.009) | 325 (0.065) |
| R8 | 0.016 | 0.015 | 0.010 | 0.008 | 0.943 | 3.725* (0.000) | 1.878* (0.034) | 292.5* (0.019) |
| R9 | 0.008 | 0.014 | -0.056 | 0.368 | 0.985 | 0.001* (0.000) | 0.947 (0.176) | 313* (0.043) |
| R10 | 0.047 | 0.114 | 0.495 | 1.385 | 0.949 | 0.007* (0.000) | -1.767* (0.044) | 432 (0.790) |
| R11 | 0.061 | 0.029 | 0.032 | 0.345 | 0.996 | 0.007* (0.000) | 0.457 (0.326) | 410 (0.554) |
| R12 | 0.057 | 0.032 | 0.028 | 0.026 | 0.788 | 1.495 (0.142) | 3.947* (0.000) | 191* (0.000) |
| R13 | 0.047 | 0.029 | 0.014 | 0.024 | 0.714 | 1.444 (0.164) | 4.823* (0.000) | 150* (0.000) |
| R14 | -0.334 | 0.631 | -0.039 | 0.365 | 0.922 | 2.985* (0.002) | -2.217* (0.016) | 278* (0.011) |
| R15 | 1.253 | 1.030 | 1.322 | 0.793 | 0.999 | 1.688 (0.082) | -0.289 (0.387) | 397 (0.433) |

**Source:** Author using SPSS

The Wilk's lambda is used in discriminant analysis and involves stepwise inclusion of predictors in the regression equation. It uses the criterion for inclusion of a predictor in the regression equation and the criterion to exclude a predictor from the regression equation.

A two-sample F-test for variances is used to check if the variances of two groups are the same or different where the $H_0$ is $\sigma_1=\sigma_2$. Based on the F test result an appropriate T test is then chosen to compare the means. If the p value from the F test is smaller than 0.05, $H_0$ is rejected and the t test assuming unequal variance is used. If the p value from F is higher than 0.05, $H_0$ cannot be rejected and the T test assuming equal variance is used.

The Mann-Whitney U-test is a non-parametric test that is used to test whether two population means are equal or not. Unlike the t-test and the F-test it does not require a special distribution of the dependent variable in the analysis and is robust against outliers and heavy tail distributions.

As seen from Table 5.3, according to the F tests seven variables R1, R2, R3, R5, R12, R13 and R15 were defined as indicators which do not have the discriminating power for sound and unsound banks. The T-test selected four insignificant variables such as R5, R9, R11 and R15. The Mann-Whitney U-test recognized 6 variables as significant. Nine variables R1, R2, R3, R4, R5, R7, R10, R11 and R15 are defined as insignificant. Thus, the current research follows the results of the F-test, T-test and the Mann-Whitney U-test given in table 5.3. The results are ambiguous that is why all 15 variables were taken into account for the construction of the MDA, logit and probit models to allow the statistical methods to choose the required variables.

### 5.4.2 Determination of Discriminant Function Coefficients

Next, discriminant function coefficients are calculated and analyzed. The values of this function should discriminate between the two groups as clearly as possible. A measure of success of this discrimination is the correlation coefficient between the calculated values of the discriminant function and the group membership indicator. Table 5.4 shows the canonical correlation coefficient for this study.

**Table 5.4: Eigenvalues**

| Function | Eigenvalue | % of Variance | Cumulative % | Canonical Correlation |
|---|---|---|---|---|
| 1 | 0.958[a] | 100.0 | 100.0 | 0.700 |

a. First 1 canonical discriminant functions were used in the analysis.
**Source:** Author using SPSS

In the Function column of Table 5.4 the value “1” indicates that one discriminant function was obtained in the course of the discriminant analysis. If the dependent variable had not two but three levels, two discriminant functions would be composed.

The high Eigenvalue (0.958) indicates that the obtained model has a high possibility of discrimination. In addition, the high index of canonical correlation (0.700) suggests a close relationship with the variables that define this index.

Table 5.5 of the Wilks' Lambda lists the indicators that determine the significance of the model obtained because of discriminant analysis.

**Table 5.5: Wilks' lambda**

| Test of Function(s) | Wilks' Lambda | Chi-square | df | Sig. |
|---|---|---|---|---|
| 1 | 0.511 | 37.976 | 3 | 0.000 |

**Source:** Author using SPSS

Wilks' Lambda is a standard statistic used to denote the statistical significance of discriminating power in the current model. Its value varies from 1.0 (no discrimination) to 0.0 (complete discrimination). Wilks' Lambda at 0.511 indicates a sufficient level of discrimination

The higher is the value of Chi-square, the stronger the discriminant function distinguishes between groups and the more effectively it fulfils its intended use. The chi-square measure of group overlap indicates that the distributions of the individual vectors of the two groups overlap substantially. Given the high degree of group overlap, the classification results are "better" than might be expected. In this case it is 37.976. Its consistency is demonstrated by the statistical significance Sig., which in this case is 0.000 and noticeably lower than 0.05.

Table 5.6 of Standardized Canonical Discriminant Function Coefficients and Table 5.7 of Structure Matrix make it possible to assess the correlation of individual independent variables used in the discriminant function with the standardized coefficients. Table 5.7 summarizes the standardized coefficients and Table 5.8 summarises the correlation coefficients.

**Table 5.6: Standardized Canonical Discriminant Function Coefficients**

| Standardized Canonical Discriminant Function Coefficients | Function |
|---|---|
| R8 | 0.443 |
| R13 | 0.974 |
| R14 | -0.869 |

**Source:** Author using SPSS

Using the standardized coefficients, the relative contribution of each independent variable in the discrimination of two study groups can be directly compared.

For example, R13 affects the financial unsoundness probability to a stronger degree than does R8.

**Table 5.7: Structure Matrix**

| | Function |
|---|---:|
| R13 | 0.647 |
| R12[a] | 0.571 |
| R6[a] | -0.380 |
| R4[a] | 0.335 |
| R14 | -0.297 |
| R10[a] | -0.282 |
| R7[a] | -0.280 |
| R3[a] | 0.255 |
| R8 | 0.252 |
| R1[a] | 0.226 |
| R2[a] | 0.214 |
| R11[a] | -0.136 |
| R15a | 0.054 |
| R5a | -0.050 |
| R9a | -0.042 |

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions

Variables ordered by absolute size of correlation within function.

a. This variable is not used in the analysis.

**Source:** Author using SPSS

Further, the discriminant function coefficients are calculated and the discriminant equation is derived based on them. They are included in Table 5.8.

**Table 5.8: Canonical Discriminant Function Coefficients**

| | Function |
|---|---:|
| R8 | 37.865 |
| R13 | 36.726 |
| R14 | -1.686 |
| (Constant) | -1.925 |

Unstandardized coefficients

**Source:** Author using SPSS

As a result, given the constant, the discriminant function equation has the form:

$$Z=-1.925 + 37.865\times R8 + 36.726\times R13 - 1.686\times R14 \quad (5.7)$$

Now, based on this equation, the probability that a bank will lose its financial soundness can be calculated.

Table 5.9 of the Functions at Group Centroids list the mean values of the discriminant function in each of the analyzed group of dependent variable.

**Table 5.9: Functions at Group Centroids**

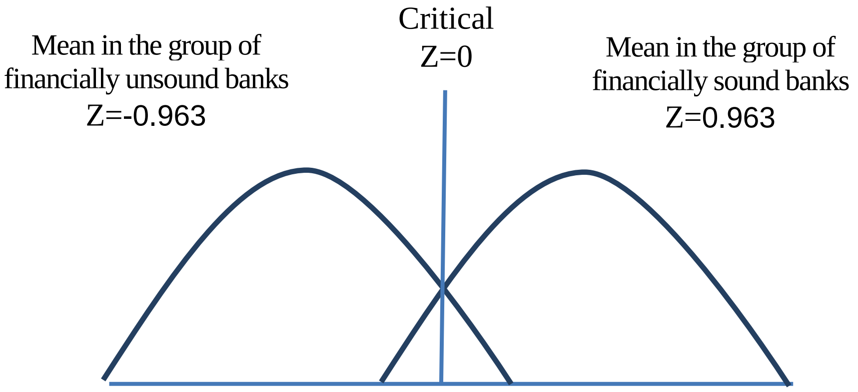
| Status | Function 1 |
|---|---|
| Sound | 0.963 |
| Unsound | -0.963 |

Unstandardized canonical discriminant functions evaluated at group means.

**Source:** Author using SPSS

Figure 5.4 shows the point for the discrimination between the two groups of financially sound and unsound banks.

**Figure 5.4: Plot of Bank Centroids with Financially Sound and Unsound Banks**




**Source:** Author

The point for discrimination in the estimated model is 0: if Z is higher than 0, the bank is financially sound; if it is less, the bank is financially unsound.

### 5.4.3 Quality Assessment of the Model

The quality of the obtained MDA model was estimated by using out-sample test with 2013, 2014 data.

Appendix 5C shows the assessment of the quality of the model for prediction of financial unsoundness of banks using the constructed MDA model on out sample period. Appendix 5C lists the assigned status Z values calculated by the formula and the predicted status of banks in 2013 and 2014.

As can be seen from Appendix 5C the MDA model has predicted the status of financially sound banks for 1 observations previously defined as financially unsound banks such as Kazkommerts bank in 2014, and the status of financially unsound banks for 3 financially sound observations of Halyk Bank of Kazakhstan, SB Sberbank and Bank Centercredit in 2013.

The classification results are summarized in Table 5.10 of Classification Results, where the last two rows provide information on the accuracy of predictions.

**Table 5.10: Out sample Classification Results**

| Default | | Predicted Group Membership | | Total |
|---|---|---|---|---|
| | | Sound | Unsound | |
| Count | Sound | 9 | 3 | 12 |
| | Unsound | 1 | 11 | 12 |
| Accuracy % | Sound | 75.0 | 25.0 | 100.0 |
| | Unsound | 8.3 | 91.7 | 100.0 |

83.3% of original grouped cases correctly classified.
**Source:** Author using SPSS

Based on Table 5.10 the classification of MDA model errors has been compiled (Table 5.11).

**Table 5.11: Classification of MDA Model Errors 2013 - 2014**

| Type of Error | Number correct | % correct | % error | Total observations |
|---|---|---|---|---|
| Type I | 11 | 91.7 | 8.3 | 12 |
| Type II | 9 | 75.0 | 25.0 | 12 |
| Total | 20 | 83.3 | 16.7 | 24 |

**Source:** Author

The results of the Multiple Discriminant Analysis in Table 5.11 show that Type I errors in the out sample period were 8.3% and Type II errors 25.0%. The overall accuracy of predictions is 83.3%. The results of the assessment of the classification correctness range from 50% to 100% so the result of 83.3% can be considered more than satisfactory.

### 5.5 Empirical Results: Logit Model

The logistic regression or logit model is a statistical model that can be used to predict the probability of an event by fitting the data to a logistic curve. Using the binary logistic regression the dependence of dichotomous variables on the independent variables that have any kind of scale can be elucidated.

In case of dichotomous variables, the question is whether a certain event can occur or not; the binary logistic regression in such case calculates the probability of an event based on the values of independent variables.

The main advantage of using the logit model is that there are no problems with the interpretation of the resulting indicator ($p$), which can have values ranging from 0 to 1 and determines the nominal value of the probability of a bank's failure.

In discriminant models the probability of bankruptcy is not determined by the nominal value. In addition, in discriminant models there commonly exists the so-called “zones of uncertainty”, from which it is impossible to draw an equivocal conclusion about the probability of bankruptcy based on the calculated indicator.

In the logit models such zones do not exist because, if the assessed probability ($p$) is greater than 0.5, it is predicted that the event will occur and, if it is less than or equal to 0.5, it is predicted that the event will not occur.

The variables used for building the logit model are the same as in the discriminant analysis (Section 5.4).

### 5.5.1 Determination of Logit Model Coefficients

The methods used are the Inclusion: Likelihood Ratios (LR) and the Exclusion: Likelihood Ratios and are stepwise. The joint criteria for the coefficients of the model are summarised in Table 5.12 of the Omnibus Tests of Model Coefficients.

**Table 5.12: Omnibus Tests of Model Coefficients**

| | | Chi-square | df | Sig. |
|---|---|---|---|---|
| Step 1 | Step | 46,861 | 4 | 0.000 |
| | Block | 46,861 | 4 | 0.000 |
| | Model | 46,861 | 4 | 0.000 |

**Source:** Author using SPSS

Chi-Square, step, block or models are the criteria for the statistical significance of the effects on the dependent variable of all predictors of a specified model, block or step. In step 1, all three criteria of Chi-square are equal for models and step because at step 1 they are identical and for block and model because the model contains only one block. Large values of the Chi-square criterion show that all included variable has a significant effect on the dependent variable.

The parameters to assess the likelihood of the model accuracy are summarised in Table 5.13.

**Table 5.13: Model Summary**

| Step | -2 Log likelihood | Cox & Snell R Square | Nagelkerke R Square |
|---|---|---|---|
| 1 | 36.316[a] | 0.542 | 0.723 |

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than 0.001.

**Source:** Author using SPSS

The value of the -2 Log Likelihood describes the model and shows how well it matches the original data. Cox and Snell's R square and Nagelkerke R square are the approximations to the value R showing the proportion of impact of all predictors of the model on the variance of the dependent variable.

In this study Nagelkerke R square is 0.723 and means that the dependent variable behaviour is explained at a level of 72.3% by the predictors included in the model.

Table 5.14 shows the effects of the inclusion of variables in the equation at each step of its compilation. The line Constant for each step corresponds to the constant **a** of the regression equation (Table 5.14).

**Table 5.14: Variables in the Equation**

| | | B | S.E. | Wald | df | Sig. | Exp(B) |
|---|---|---|---|---|---|---|---|
| Step 1[a] | R5 | -0.516 | 0.296 | 3.033 | 1 | 0.082 | 0.597 |
| | R8 | -245.762 | 101.767 | 5.832 | 1 | 0.016 | 0.000 |
| | R13 | -119.94 | 41.915 | 8.188 | 1 | 0.004 | 0.000 |
| | R14 | 3.804 | 1.366 | 7.758 | 1 | 0.005 | 44.898 |
| | Constant | 9.794 | 3.476 | 7.938 | 1 | 0.005 | 17931.929 |

a. Variable(s) entered on step 1: R5, R8, R13, R14.

**Source:** Author using SPSS

Wald chi-square tests the null hypothesis that the B coefficient or constant equals 0. If the p-value from the column sig. is less than 0.05 the hypothesis is rejected and B coefficient or constant is not 0. Exp(B) is an odds ratio and is the exponentiation of the B coefficient. P values for all ratios and constant are less than 0.05. Based on the Wald chi-square test and its p-value (Sig.) all coefficients of the logit model are statistically significant. Thus, equation Z will be:

$$Z_{lfs} = -0.516\times R5 - 245.762\times R8 - 119.94\times R13 + 3.804\times R14 + 9.794 \qquad (5.10)$$

### 5.5.2 Assessment of Logit Model Quality

An out sample test with 2013, 2014 data was applied to assess the quality of the constructed logit model. The calculated probability values and the prediction of distribution into groups are listed in Appendix 5D.

As it can be seen from Appendix 5D, the Logit model has predicted the status of financially sound banks for 1 cases previously defined as financially unsound such as TemirBank in 2014 and the status of financial unsound banks for 2 financially sound observations for Halyk Bank of Kazakhstan and Bank Centercredit in 2013.

The comparison of predicted values for the dependent variable based on the logit model and the assigned status is shown in the Classification Table 5.15.

**Table 5.15: Out Sample Classification Table**

| Observed | Predicted | | |
|---|---|---|---|
| | Sound | Unsound | Percentage Correct |
| Sound | 10 | 2 | 83.3 |
| Unsound | 1 | 11 | 91.7 |
| Overall Percentage | | | 87.5 |

**Source:** Author using SPSS

As the data in the last column of the Table 5.16 show, the results of prediction proved to be correct for 87.5% of objects. It is more convenient to interpret the results in the form of the following indicators in Table 5.16.

**Table 5.16: Table of Classification of Logit Model Errors**

| Type of Error | Number Correct | % Correct | % Error | Total Observations |
|---|---|---|---|---|
| Type I | 11 | 91.7 | 8.3 | 12 |
| Type II | 10 | 83.3 | 16.7 | 12 |
| Total | 21 | 87.5 | 12.5 | 24 |

**Source:** Author

Table 5.16 shows that Type I errors are 8.3% and Type II errors are 16.7%. A total of 87.5% of cases are classified correctly. The predictive ability of the model is high.

### 5.6 Empirical Results: Probit Model

In the probit analysis, the probability of banks falling in to one of two groups is presented as a function of the normal distribution:

$$P_{pa} = \int_{-\infty}^{Z_{pa}} \frac{1}{\sqrt{2\pi}} e^{\frac{-z}{2}} dz \qquad (5.12)$$

#### 5.6.1 Determination of Probit Model Coefficients

The statistics provided in Table 5.23 generated in Eviews will help to assess the quality of the model; coefficients for the calculation of Zpa are also provided there.

Table 5.17 includes the statistics, which can be used to assess the significance of the probit model. All coefficients of the probit model are statistically significant, as seen from the z-statistics.

**Table 5.17: Test Statistics for Probit Model**

| | | | | |
|---|---|---|---|---|
| Dependent Variable: STATUS | | | | |
| Method: ML - Binary Probit (Quadratic hill climbing) | | | | |
| Date: 06/29/17 Time: 09:38 | | | | |
| Sample: 1 60 | | | | |
| Included observations: 60 | | | | |
| Convergence achieved after 6 iterations | | | | |
| Covariance matrix computed using second derivatives | | | | |
| Variable | Coefficient | Std. Error | z-Statistic | Prob. |
| C | 3.247906 | 0.963978 | 3.369273 | 0.0008 |
| R8 | -75.34322 | 33.15429 | -2.272503 | 0.0231 |
| R13 | -65.96576 | 21.40151 | -3.082294 | 0.0021 |
| R14 | 2.474162 | 0.869999 | 2.843868 | 0.0045 |
| McFadden R-squared | 0.528058 | Mean dependent var | | 0.5 |
| S.D. dependent var | 0.504219 | S.E. of regression | | 0.345668 |
| Akaike info criterion | 0.787584 | Sum squared resid | | 6.691236 |
| Schwarz criterion | 0.927207 | Log likelihood | | -19.62751 |
| Hannan-Quinn criter. | 0.842198 | Deviance | | 39.25503 |
| Restr. Deviance | 83.17766 | Restr. log likelihood | | -41.58883 |
| LR statistic | 43.92263 | Avg. log likelihood | | -0.327125 |
| Prob(LR statistic) | 0 | | | |
| Obs with Dep=0 | 30 | Total obs | | 60 |
| Obs with Dep=1 | 30 | | | |

**Source:** Author using Eviews

Zpa equation takes the following form:

$$Zpa = 3.247906 - 75.34322 \times R8 - 65.96576 \times R13 + 2.474162 \times R14 \qquad (5.13)$$

When determining the predicted status, the probit model calculates the probability for each object and, based on this probability, assigns to a bank one of the two values of the dichotomous variable. If the probability is less than 0.5, the bank is assessed as financially sound (the value of the variable "status" is set to 0): otherwise, the bank is financially unsound (the value of the variable "status" is set to 1).

### 5.6.2 Assessment of Probit Model Quality

The values of Zpa, the probability and the status of banks calculated for the out sample period 2013-2014 based on the constructed probit model are listed in Appendix 5E.

As we can see from Appendix 5E, the probit model has predicted the status of financially sound banks for 1 case previously defined as financially unsound banks such as Kazkommerts bank in 2014 and the status of financially unsound banks for 3 financially sound observations of Halyk

Bank of Kazakhstan, SB Sberbank and Bank Centercredit in 2013.

The quality of the assessed probit model and the correctness of classification in 2013 – 2014 are summarised. Based on the predicted status and percentage of correct observations, the classification of errors in out sample period in Table 5.18 has been compiled.

**Table 5.18: Classification of the Probit Model Errors**

| Type of Error | Number Correct | % Correct | % Error | Total Observations |
|---|---|---|---|---|
| Type I | 11 | 91.7 | 8.3 | 12 |
| Type II | 9 | 75.0 | 25.0 | 12 |
| Total | 20 | 83.3 | 16.7 | 24 |

**Source:** Author

Thus, the probit model has 8.3% of Type I errors and 25.0% of Type II in 2013 – 2014 years. A total of 83.3% of the observations are classified correctly. This indicates a high predictive ability of the probit model in out sample period.

In summary, MDA and probit models in the out sample period obtained above demonstrate high predictive accuracy at 83.3%. The logit model out performed other models and its predictive ability was 87.5%

High predictive accuracy of models is satisfactory. Nevertheless the cut-off points were moved to improve the models' performance and the results of the three models were joined and reported in Table 5.22.

**Table 5.19: Cut-off Points of the MDA, Logit and Probit Models**

| Percen-tile | MDA | | | Logit | | | Probit | | |
|---|---|---|---|---|---|---|---|---|---|
| | Predictive accuracy | Type I | Type II | Predictive accuracy | Type I | Type II | Predictive accuracy | Type I | Type II |
| 25 | 75.00% | 50.00% | 0.00% | 75.00% | 0.00% | 50.00% | 79.17% | 0.00% | 41.67% |
| 30 | 79..17% | 41..67% | 0.00% | 79.17% | 0.00% | 41.67% | 83.33% | 0.00% | 33.33% |
| 35 | **87.50%** | **25.00%** | **0.00%** | 87.50% | 0.00% | 25.00% | 83.33% | 0.00% | 33.33% |
| 40 | 83.33% | 25.00% | 8.33% | **91.67%** | **0.00%** | **16.67%** | 87.50% | 0.00% | 25.00% |
| 50 | **87.50%** | **16.67%** | **8.33%** | 87.50% | 8.33% | 16.67% | 87.50% | 8.33% | 16.67% |
| 55 | **87.50%** | **8.33%** | **16.67%** | **91.67%** | **8.33%** | **8.33%** | 91.67% | 8.33% | 8.33% |
| 60 | 83.33% | 8.33% | 25.00% | **91.67%** | **16.67%** | **0.00%** | **95.83%** | **8.33%** | **0.00%** |
| 65 | 79.17% | 8.33% | 33.33% | 87.50% | 25.00% | 0.00% | 83.33% | 33.33% | 0.00% |
| 70 | 79.17% | 0.00% | 41.67% | 79.17% | 41.67% | 0.00% | 83.33% | 33.33% | 0.00% |
| 75 | 75.00% | 0.00% | 50.00% | 75.00% | 50.00% | 0.00% | 75.00% | 50.00% | 0.00% |

**Source:** Author

New cut-off points improved the quality of all models. The predictive ability of the MDA model increased from 83.3% to 87.5%, Type II errors decreased from 25.0% to 16.7% and Type I errors remained unchanged. The predictive accuracy of the logit model improved from 87.5% to 91.67%, Type II errors remain at 16.7% and Type I errors decrease from 8.3% to 0%. The most significantly the predictive ability of the probit model improved from 83.3% to 95.83%, Type II errors decreased from 25.0% to 0%, Type I errors remain at 8.3%.

### 5.7 Empirical Results: Integrated Prediction Model of Bank Unsoundness

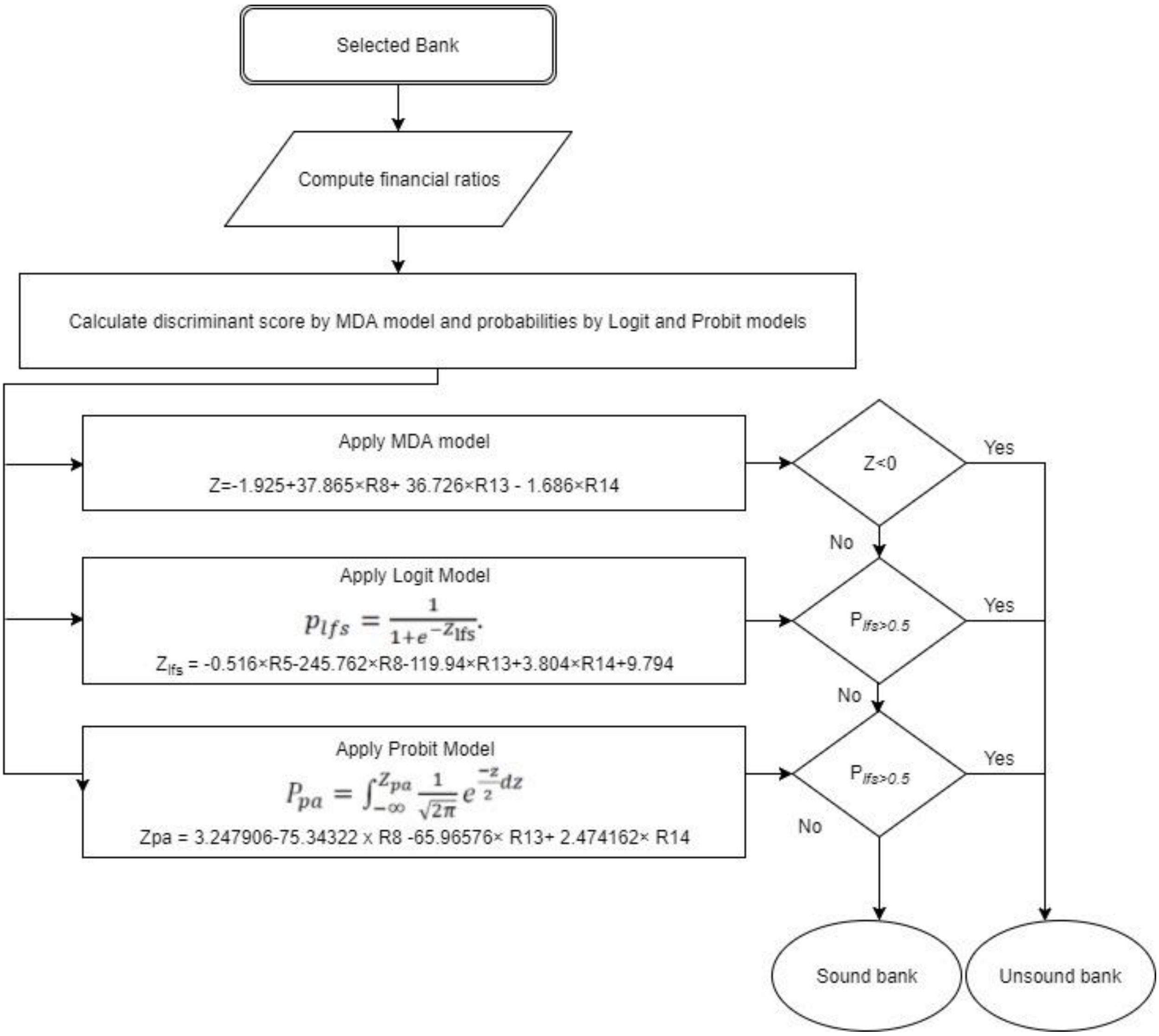
Research devoted to enhance the prediction models has increased and some studies which integrate and compare two or more models have appeared. Lee (1990) was one of the first researchers who integrated two models in decision support systems areas and noted that integration can synergistically benefit both. He affirmed that integration implies the unification of problem specifications and solution procedures which encompass both integrating methodologies. Jo and Han (1996) suggested the use of integrated model that used a combination of discriminant analysis, neural network and case-based forecasting system. They used the bankruptcy prediction to validate the effectiveness of the integrated model and the prediction ability of the integrated model was superior to the three independent prediction techniques. So, they concluded that the prediction error was reduced when the prediction results of various methods were combined.

Also, Lam and Moy in 2002 presented a method which combines several discriminant methods to predict the classification of new observations. They drew conclusions that as, no single-discriminant method outperforms other discriminant methods under all circumstances, decision-makers may solve a classification problem using several discriminant methods and examine their performance for classification purposes in the training sample.

The current study tries to improve the predictability of the three empirical models of MDA, logit and probit obtained above. They can be systematically combined together to construct an integrated prediction model of bank financial unsoundness as a reliable decision tool in bank supervision and examination. This model could help to increase the probability of correct forecasting.

Figure 5.5 shows the structure of the integrated prediction model of bank financial unsoundness and its data flow. Basically the predicted values from the three models are employed to be the input variable of the integrated model. The processes of the integrated model are presented in the view of the data flow. The model consists of four types of data namely (i) four variables, (ii) computed coefficients of MDA, logit and probit models, (iii) predicted value of discriminant score by MDA model and probabilities by logit and probit models, (iv) prediction output (sound/unsound bank).

**Figure 5.5: Flow Chart of the Integrated Prediction Model of Bank Unsoundness**




**Source:** Author

When assessing a new bank according to the integrated model, all the system data will remain unchanged, except for 4 financial ratios of the analyzed bank. These ratios are the base for MDA, logit and probit models. Hence, the input to the system consists of 4 ratios which are used in calculating the discriminant score, logit and probit probability of bank unsoundness. The system provides early warning signals for each of the discriminant, logit and probit models. These three empirical models together increase prediction accuracy about the future problem of the bank. The integrated model assigns unsound status for a bank if even one of the three models predict bank as unsound. For example, the estimated discriminant score for Kazkommerts bank on 1st January, 2014 is 0.096 which is lower than the cut-off score. The estimated logit and probit unsoundness probability for this bank are 69.0% and 44.3% respectively. So, according to the MDA and Probit model, this bank is sound, according to Logit model it is unsound. Thus, the Logit model gives true information about this bank, which actually is unsound in 2014. The integrated model assigns the status of unsound for this bank also. So, the integrated model gives more cautious and conservative forecasts that should reduce the Type I errors. The ability to detect bank unsoundness will reduce the cost of monitoring and provide valuable information to the supervisor to prevent bank failure.

The integrated model determined the predicted statuses for each case from 1st January, 2013 to 1st January, 2014 as presented in Appendix 5F.

It can be seen from Appendix 5F, the integrated model has predicted the status of a financially unsound for 3 financially sound observations of the Halyk Bank of Kazakhstan, the SB Sberbank and the Bank Centercredit in 2013.

The classification results of the integrated model on out sample data for predictive accuracy, Type I and Type II errors are shown in Table 5.19.

**Table 5.20: Table of Classification of Integrated Bank Unsoundness Prediction Model Errors, 2013 – 2014**

| Type of Error | Number Correct | % Correct | % Error | Total Observations |
|---|---|---|---|---|
| Type I | 12 | 100.0 | 0.0 | 12 |
| Type II | 9 | 75.0 | 25.0 | 12 |
| Total | 21 | 87.5 | 12.5 | 24 |

**Source:** Author

Table 5.19 shows that the predictive accuracy of the integrated model in out sample period is high. Type I errors are absent and Type II errors are 25.0%. A total of 87.5% of cases are classified correctly. The integrated model did not outperform the MDA model by overall predictive accuracy. However, it reduced the rate of Type I errors in comparison with the MDA, logit and probit models. As known, Type I errors are more costly than Type II errors.

## 5.8 Empirical Results: Comparative Analysis of Predictive Ability of the MDA, Logit, Probit and Integrated Models

Comparative analysis starts by examining the accuracy of the models in predicting bank unsoundness that occurred during the sample period. This chapter focused on three statistical models in an attempt to evaluate their effectiveness with respect to each other in addition to an integrated model based on the three of them. Four criteria will be used to assess the performance of these models, namely:

- percentage of Type I errors;
- percentage of Type II errors;

- predictive ability of the model.

This section analyses the predictive ability of three empirical models and the integrated model. Prior studies conclude that integrated models produce higher prediction accuracy than individual models (Jo and Han, 1996). Results from this study are in line with these findings (Table 5.20).

**Table 5.21: Comparative Quality Assessment of Models**

| | MDA model | Logit model | Probit model | Integrated model |
|---|---|---|---|---|
| Failed banks correctly predicted | 11 | 11 | 11 | 12 |
| Non-failed banks correctly predicted | 9 | 10 | 9 | 9 |
| Type I error | 1 | 1 | 1 | 0 |
| Type II error | 3 | 2 | 3 | 3 |
| Incorrectly predicted in total | 4 | 3 | 4 | 3 |
| Correctly predicted in total | 20 | 21 | 20 | 21 |
| % of failed banks correctly predicted | 91.7 | 91.7 | 91.7 | 100 |
| % of non-failed banks correctly predicted | 75.0 | 83.3 | 75.0 | 75.0 |
| % of total incorrectly predicted | 16.7 | 12.5 | 16.7 | 12.5 |
| %Type I error | 8.3 | 8.3 | 8.3 | 0 |
| %Type II error | 25.0 | 16.7 | 25.0 | 25.0 |
| % of total correctly predicted | 83.3 | 87.5 | 83.3 | 87.5 |

**Source:** Author

All employed models demonstrated high overall predictive accuracy in 2013 – 2014 years. MDA and Probit models at 83.3%, Logit and Integrated Models at 87.5%. Integrated model showed the lowest rate of Type I errors at 0.0% Logit Model had the lowest rate of Type II errors at 16.7%. The MDA, probit and logit models' Type I errors are 8.3% and Type II errors are 25.0% for MDA and Probit Models and 16.7 for Logit Model. The integrated model had the expected lowest rate of Type I errors at 0.0%, Type II errors are 25.0%. All models were effective in predicting unsoundness status of banks but the integrated model insignificantly outperformed MDA, logit and probit models in Type I errors.

The loss from Type I errors is significantly larger than that of Type II errors because Type I error occurs when the bank with a prediction of financially sound defaults, while Type II error implies that the bank with a prediction of financially unsound survives. Sahajwala and Van den Berg (2000) confirm that Type I error is potentially more serious than Type II error because a weak bank that may escape supervision entails a higher risk. Supervisory authorities aim at minimizing the Type I error rate and calibrating models to carry a low Type I error. So, the integrated model demonstrated superior results, reducing Type I errors to 0.0%.

Jo and Han (1996), Lam and Moy (2002), Canbas, Cabuk, and Kilic (2005) and Othman (2013) affirmed that several models together provide superior information about the future prospect. The results of this study show that an integrated model decreases Type I error.

Indeed, two approaches of discriminant analysis and choice are compared in terms of the predictive power in prior studies. In those of Lennox (1999) and Lin (2009) the authors noted the superiority of the logit model and in the studies of Altman et al. (1994) and Jagitiani (2003) the authors did not find a significant difference in the predictive power of the two approaches. The results of the current study are consistent with both the first and second findings because the predicted values of these models are very close but the predictive power of the logit model is a little higher.

This study concludes that an integrated model can be used to form a successful costless supervision tool and is able to detect unsound banks over long periods of time without modification. This means that the signal indicators used by the models to detect unsound banks must be stable over long periods of time. At the same time, it also finds that all models studied do an efficient job of detecting signals of bank unsoundness within five years and could be used as successful predicting techniques.

The power of these empirical models lies in the indicators used by them. Focusing on the ability of financial ratios to highlight those banks that prove to be vulnerable to financial distress, the four variables reflecting capital adequacy, management, operating efficiency and liquidity were chosen. In the models using the MDA, logit and probit analysis, the significant coefficients calculated were the R13 interest rate spread and the R14 working capital to total assets ratio. MDA and logit analysis considers one more ratio of R8 salary to assets. The logit model additionally considers the R5 debt to equity ratio.

The R13 interest rate spread is calculated as the difference between the average interest rate paid to depositors and the average interest rate earned from borrowers. This indicator reveals bank operating efficiency and allows a superior understanding of the sources of bank profitability and hence the degree of vulnerability of its profitable sources. A negative or very low value indicates an ineffective interest rate policy or a loss but a high value also could be a negative sign because high rates are often earned on assets that are excessively risky.

The R14 net working capital to total assets is used to measure liquidity. It is an indicator from the modified Altman four-factor model for non-manufacturing companies. It is calculated as the ratio of net working capital to total assets. Working capital is the difference between current assets and current liabilities. Altman (1968) considered this indicator as the most valuable of the three liquidity ratios.

Rahman et.al. (2004) proved that capital adequacy, loan management and operating efficiency are three common performance dimensions able to identify problem banks. This result comes as no surprise as banks that have a high R5 debt to equity ratio are more fragile during the crisis. Estrella, Park and Perisitiani (2000) suggest using simple coefficients such as leverage to predict bank failure as a very informative indicator. Also, sometimes, less frequently mentioned indicators have a higher ability to discriminate depending on the particular situation and may change over time (Ohlson, 1980). In this case they are R8 salary to assets ratio.

These four early indicators could provide supervisory bodies with a head start in identifying the root cause of changes in a bank's financial soundness and could potentially enhance off-site monitoring effectiveness. Understanding the root cause of a bank's unsoundness is likely to enhance the effectiveness of bank monitoring and supervision.

### 5.9 Summary

This Chapter analysed the ability of three statistical models in predicting the financial soundness of banks, namely the MDA, logit, probit models. In addition, it developed an integrated model based on these three models. Firstly, the explanatory power of the independent variables and the correlation between them were assessed. Next the MDA, logit and probit models were constructed and integrated in order to find the most reliable model by exploring their predictive ability. Finally, the comparative analysis of the predictive ability of the empirical models was carried out.

The empirical results of this Chapter are listed in the following:

1. In the out sample period the MDA model has predicted the status of financial soundness for 1 observation previously defined as financial unsound banks such as Kazkommerts bank in 2014 and the status of financial unsound banks for 3 financial sound observations of Halyk Bank of Kazakhstan, SB Sberbank and Bank Centercredit in 2013.

For the Multiple Discriminant Analysis model, in out sample period in 2013 – 2014 years Type I errors in the model were 8.3% and Type II errors 25.0%. The overall accuracy of predictions is 83.3%.

2. The Logit model has predicted the status of financial soundness for 1 cases previously defined as financial unsound banks such as TemirBank in 2014 and the status of financial unsoundness for 2 financial sound observations of the Halyk Bank of Kazakhstan and Bank

Centercredit in 2013.

Type I errors are 8.3% and Type II errors are 16.7% in the out sample period in 2013 – 2014 years. A total of 87.5% of cases are classified correctly. The predictive ability of the model is high.

4. The Probit model has predicted the status of financial soundness for 1 case previously defined as financial unsound banks such as Kazkommerts bank in 2014 and status of financial unsoundness for 3 financial sound observations of Halyk Bank of Kazakhstan, SB Sberbank and Bank Centercredit in 2013.

The Probit model has Type I errors at 8.3% and Type II errors at 25.0%. In general, 83.3% of observations have been classified correctly in 2013 - 2014.

5. The integrated model has predicted all unsound banks correctly, but it assigned status of financial unsoundness for 3 financially sound observations of the Halyk Bank of Kazakhstan, the SB Sberbank and the Bank Centercredit in 2013.

In 2013 – 2014 the integrated model has no Type I errors and its Type II errors are at 25.0%. A total of 87.5% of cases are classified correctly.

6. All constructed models demonstrated high predictive ability. The logit and integrated models had the superior overall predictive ability to forecast bank financial unsoundness in comparison with the MDA and Probit Models. The predictive ability of the integrated model was equal to the logit but it proved its superiority in Type I errors. This research has confirmed the conclusions of Jo and Han (1996), Canbas, Cabuk, and Kilic (2005) and Othman (2013) that when the prediction results of various methods were combined the prediction accuracy were improved.

# CHAPTER 6 CONCLUSION

## 6.1 Introduction

The functioning of banks in a constantly changing economic environment is accompanied by risks, and the severity of a negative impact on an economy largely depends on the level of financial soundness. Therefore, the soundness of the banking system plays a crucial role in the development of any economy. The Kazakh banking system had enjoyed rapid development and success before the world financial crisis. It was considered the most efficient and the optimal system among the former Soviet countries. In the first years the impact of the crisis was minimal and it seemed to be overcome (IMF, 2014). However, by 2014 the share of banking sector assets to GDP had severely dropped to 44% and NPL had mounted to 36%. Therefore, the need for reliable early warning signals about the financial soundness of the banking system seems crucial. Recent cases of restructuring, nationalization and bank mergers require a reliable system of assessment of the financial soundness of the banking system as a whole and individual banks in particular.

An assessment of the financial soundness of banks helps the policy maker to identify the strengths and weaknesses of banking systems and assists them in adopting appropriate supervisory policy. In this context, the purpose of the current study is to explore, empirically assess and analyse the financial soundness of the banking sector in Kazakhstan and predict financial unsoundness at bank level. The study first presents a general overview of the financial soundness in the Kazakh banking sector. It then investigates the applications of verified statistical techniques such as PCA, cluster analysis, MDA, logit and probit analyses in three empirical chapters.

This chapter summarises the results and gives conclusions of the thesis. Section 6.2 provides answers to the research questions. Sections 6.3 and 6.4 summarises the findings obtained and their implementation. Sections 6.5 and 6.6 discuss the limitations of the study and the possibilities for future research. This study proposes that the Kazakhstan supervisory and monitoring authorities consider and employ two additional reliable tools of a cluster based methodology for assessing the financial soundness of the banking sector and an integrated model for the prediction of individual bank financial unsoundness.

## 6.2 Answering the Research Questions

This section provides the findings of the empirical chapters presented in this thesis as answers to three research questions (RQ).

**RQ 1 Can cluster analysis identify the structure of the banking sector according to the**

**extent of financial soundness?**

The findings in Chapter 3 provide an answer to the first research question. The researcher employed a cluster based methodology to assess the financial soundness of the banking sector. It was developed and proposed for use by the regulatory and supervisory authorities to identify the structure of banking sector. This methodology involves the following 5 stages to determine sound and unsound banks:

Step 1. **Preparation**: selection of indicators and data collection.
Step 2. **Descriptive Analysis**: short description of each ratio and demarcation of limits of financial soundness.
Step 3. **Principal Component Analysis**: analysis of correlation of variables, extraction of principal components and rotation of components to simplify structure and interpretation of components.
Step 4. **Clustering of the Banking Sector by Extent of Financial Soundness**: cluster identification and calculation of financial ratio medians for each cluster.
Step 5. **Interpretation of Clusterisation Results:** final grouping of clusters using limits of financial soundness; interpretation of structure of banking sector by the degree of financial soundness for **sound / unsound banks**.

Some CAMELS indicators were selected to reflect the main characteristics of capital adequacy, assets quality, management, earnings and liquidity. A set of 15 financial variables which act as a proxy for the five CAMELS components is identified.The selection of these ratios is widely based on a review of prior studies that examine the financial soundness of banks, distress, failure and bankruptcy. These financial ratios are also a part of the IMF FSI and Kazakhstan banks' prudential norms. Data are collected from the reports of The National Bank of Kazakhstan and from the annual financial statements of all commercial Kazakhstan banks for the period from 1st January, 2008 to 1st January, 2014. The research sample consists of all Kazakhstan banks, represented by 34 banks on 1st January, 2008, and 37 banks on 1st January, 2014. The former was chosen to represent the pre-crisis date and the latter as the final most recent date with fully available data.

Based on the results of the PCA, 12 indicators were isolated from 15. They represent 5 principle components of capital adequacy, return on assets, profitability, asset quality (NPL), liquidity and leverage.

Then clustering of banking sector by the extent of financial soundness was performed based on these 5 principal components by the k-means method.

The proposed methodology diagnosed the dramatic deterioration of the structure of the banking sector according to the extent of their financial soundness. On 1st January, 2008 there were no unsound banks in Kazakhstan. Risky banks were 44% of the total, those of sound were 56%. On 1st January, 2014, unsound banks were 16%, risky banks were 60% and sound banks were 24%.

**RQ 2 Can Altman models adequately predict bank financial unsoundness?**

Chapter 4 answered the second research question and demonstrated that Altman models had modest ability to predict bank financial unsoundness in Kazakhstan banks and they should be used cautiously.

Chapter 4 analysed whether Altman models are efficient in the prediction of the financial unsoundness of Kazakhstan's banks. This chapter examined two of Altman's models: Z (1993) – the Four-Factor Altman Model for non-manufacturing companies and EM Score (1995) – the Four-Factor Altman Model for emerging markets on Kazakhstan banks in order to assess their ability to predict financial unsoundness. Annual data from 12 Kazakhstan banks across the period from the 1st of January, 2008 to the 1st of January, 2014 were selected. The sample consisted of 6 financially sound and 6 unsound banks. Sound banks were isolated from group of financial sound banks taking into account their assets' size, specialization and branch network.

Since Altman models were used for prediction of financial unsoundness and not bankruptcy, the cut-off points for testing the original models were changed and the 'grey zone' were joined to zone of a high probability of bankruptcy. These two zones formed the zone of financially unsound banks. Then, in line with Moyer (1977), Merkevicius et al. (2006), Wu et al. (2010) and Ho et al. (2013), both models were re-estimated to improve their predictability. The first approach included in the discriminant function each of the four variables specified by Altman. The second approach was a stepwise method which enters variables into the function in a stepwise manner up to the point where the Wilks' lambda is minimized. The Cut-off points were changed to increase the predictive accuracy.

The results indicated that the original Z (1993) for non-manufacturing companies and EM Score (1995) for emerging markets have low predictability at 45.2% and 44.1%. The Cut-off values for original models were changed to reduce Type I and Type II errors. The best cut-off points for both models were found at 93 percentile. It improved predictive accuracy to 52.38% and significantly decreased Type I errors. Further re-estimating the Z-score using two methods improved the accuracy of prediction to 63.1% and 61.9%. New cut-off points for both models improved predictive accuracy to 70.24% for $Z_D$ model and 69.05% for $Z_W$.

However, the predictive accuracy of the original and re-estimated models is weaker than results obtained by recent studies of Xu and Zhang (2009), Wu et al. (2010), Vaziri et al. (2012), Othman (2013), Chieng (2013), Ho et al. (2013), Rankov and Kotlica (2013) and Pradhan (2014).

**RQ 3 Can the predictability of bank financial unsoundness be improved by using statistical models such as MDA, Logit and Probit?**

Chapter 5 is the third empirical section which attempted to improve the predictability of bank financial unsoundness by using statistical models such as MDA, Logit and Probit. These models were constructed on the sample of 12 Kazakhstan banks for the period from 1st January, 2008 to 1st January, 2014. 1st January 2014 is used as a benchmark. This sample consisted of 6 sound and 6 unsound banks and accounts for 81.3% of the total assets of the banking sector. Data were collected from the annual financial reports. Then, the three empirical models of MDA, logit and probit were systematically combined together to construct an integrated model of predicting bank financial unsoundness.

The MDA model showed a high possibility of discrimination with Eigenvalue at 0.958 and suggests a close relationship with the variables with a high index of canonical correlation at 0.700. The overall accuracy of prediction is 83.3%.

The logit model showed a high possibility to explain the variance of the dependent variable. In this study, the Nagelkerke R square was 0.723. In total, 87.5% of the observations have been classified correctly, Type I errors are 8.3% and Type II errors are 16.7%.

All coefficients of the probit model are statistically significant, as seen from the z-statistics. In general, 83.3% of observations have been classified correctly, Type I errors are at 8.3% and Type II errors at 25.0%.

In order to improve the predictive accuracy of MDA, logit and probit models the cut-off points were calibrated by percentile. New cut-off points improved the quality of all models. The predictability of the MDA model increased from 83.3% to 87.5%, Type II errors decreased from 25.0% to 16.7% and Type I errors remained unchanged. The predictive accuracy of the logit model improved from 87.5% to 95.8%, Type II errors decreased from 16.7% to 0%, Type I errors remain at 8.3%. Also, the predictability of the probit model improved from 83.3% to 95.8%, Type II errors decreased from 25.0% to 0% and Type I errors remain at 8.3%.

The proposed integrated model used unchanged data except for the financial ratios of the analysed banks. These ratios are the base for calculating the four components using the MDA, logit and probit models. Hence, the input to the system consists of four ratios which are used in calculating the discriminant score and the logit and probit probability of bank unsoundness. The system provides early warning signals for each of the discriminant, logit and probit models.

These three empirical models together increase the prediction accuracy about the future problem of banks.

The final result of the integrated model has Type I errors at 0% and Type II errors at 25.0%. In general 87.5% of observations have been classified correctly. The integrated model has predicted the status of financial unsoundness for 3 financially sound observations of the Halyk Bank of Kazakhstan, the SB Sberbank and the Bank Centercredit in 2013.

This study concludes that an integrated model can be used as a successful, costless supervision tool which is able to detect unsound banks over long periods of time without modification. This means that the signal indicators used by the models to detect unsound banks must be stable over long periods of time. At the same time, it also finds that all models studied in Chapter 5 successfully detect signals of bank unsoundness within five years and could be used as reliable predicting techniques.

### 6.3 Implementation of Findings

This study presents novel theoretical and empirical results of the financial soundness of the Kazakhstan banking industry. It also provides some empirical justification for introducing new statistical techniques as regulatory tools. This study suggests a cluster based methodology and a number of early warning models, including important variables, should be taken into consideration when designing early warning models for Kazakhstan banks. The following contributions to knowledge can be gleaned from this study:

1. A review of prior studies shows that there is no universally agreed definition of the concept of financial soundness. Researchers tend to consider financial unsoundness as an earlier step of distress. Thus, the earlier the detection of bank financial unsoundness, the more likely is it that a bank will avoid bankruptcy.

This study followed Pukhov’s (2013) concept of financial soundness. Financial soundness is a bank's condition in which the indicators characterizing capital adequacy, asset quality and liquidity, as well as the effectiveness, are within certain limits, and the transition beyond this leads a sound bank in to unsound status. Thus, financial unsoundness of the bank is a condition in which the indicators characterizing capital adequacy, asset quality, liquidity and efficiency extend beyond certain limits. These limits were obtained as the result of a descriptive analysis. Demarcation of financial soundness limits was made by quartile intervals based on the medians of ratios for each bank.

2. In order to establish a powerful and efficient supervision system for the banking industry, it is necessary to recognize sound and unsound banks. Earlier detection of bank unsoundness helps maintain the sustainability of the financial system.

A proposed cluster based methodology proved its ability to identify a banking sector structure by the extent of the financial soundness of its banks and could be used as a reliable technique to detect early signs of deterioration in the banking system. Unsound banks had a low level of capital adequacy, a low net interest rate margin and interest rate spread, the lowest quality of assets and return on assets and the highest debt to equity ratio. There was a marked deterioration in the quality of assets with a high level of NPL to total gross loans and capital.

3. Each of the MDA, logit and probit models are employed to examine their ability to predict the financial unsoundness of banks. The results indicate that all these models are able to predict bank financial unsoundness even during the financial crisis. Thus, this shows the high predictive accuracy of the models per se, and more importantly the ability of the models to recognise banks which are in unsound status even in the period of volatility. The proposed integrated model which is introduced in Chapter 5 had a high predictability. The integrated model did not outperform the MDA and logit models by overall predictive accuracy. However, its indisputable advantage is in reducing the rate of Type I errors in comparison with other models. In terms of identifying unsound banks, the integrated model provides some evidence that it outperforms the other models by identifying unsound banks as early as three years prior to the benchmark.

With the performance of the integrated model, the researcher comes to a conclusion that it can be viewed as the superior complementary instrument for monitoring Kazakhstan banks. This integrated model can serve as a reliable tool to support decision-making in bank supervision and examination in Kazakhstan.

4. Understanding the sound and unsound status of banks could help supervisory bodies when conducting a comprehensive evaluation of the financial health of the entire banking industry and individual banks. In terms of bank monitoring, the supervisory authorities can use a selected set of 15 indicators that is examined in this study. These indicators were used both in previous research and in international systems for the assessment of bank financial soundness such as BASEL, CAMELS and FSI.

The MDA, logit, probit and the proposed integrated models used such financial ratios as the R5 debt to equity ratio, the R8 salary to assets, the R13 interest rate spread and the R14 working capital to total assets ratio as indicators of bank unsoundness. Hence, it is recommended that Kazakhstan policy makers pay more attention to these four monitoring indicators when evaluating performance in order to discover vulnerable banks.

This study suggested a number of recommendations on assessing the financial soundness of banks for regulation purposes so as to design a proper and timely policy that reduces bank failure. It suggests that a cluster based methodology and an integrated model can detect bank distress. These techniques are neutral and objective complementary instruments.

The main conclusions and recommendations of the study can serve as a basis for further academic research and can be used in university disciplines by students studying banking.

### 6.4 Limitations of the Research

The first limitation of this study is the reliance on some subjective thresholds as minimum ratio values. Demarcation of financial soundness limits allows the setting of limits for the coefficients by the degree of bank financial soundness for a banking sector at particular time. The calculated limits are not claimed to be the general limits. This technique is a useful tool for the grouping of banks by the degree of financial soundness in countries where not all banks have reliable credit ratings. For example, in Kazakhstan, during the last fifteen years just 12 to 26 banks from 38 received ratings from Standard & Poors, Fitch or Moody's according to the Kazakhstan Stock Exchange (kase.kz).

Obviously, if financial soundness is considered, the banks of developed countries will have higher indicators than those in developing countries. For example, the standards of high financial soundness for banks in the USA and Europe are completely different from banks in Kazakhstan. Thus thresholds of financial soundness indicators are specific to each country. The proposed methodology identifies the structure of a banking sector of any country and calculates individual thresholds for the indicators of bank financial soundness for the specific country.

Despite the subjectivity of the obtained limits of financial soundness they are a significant advantage. The proposed cluster based methodology set these limits for Kazakhstan banks and they reflect the real situation in the Kazakhstan banking sector. Moreover, this methodology is suitable and helpful in setting limits for every banking sector of any country. According to Sclove (2001) and Marsh et al. (2003), clustering depends on the specification of the variables, the measure of dissimilarity or similarity, and the clustering procedure. There is no right or wrong solution with cluster analysis but only different viewpoints of the same set of data. The subjectivity is implicit in the process of analysis in general.

Second, the quality of the assessment of financial soundness depends on the quality of the source data. In this regard the study had certain limitations. The method of data collection for the quantitative study was limited to secondary sources. The researcher could not control the quality of information from the prudential norm reports of the National Bank and the financial statements of banks. The value of some indicators over certain periods were not available for the study. Financial statements of restructured banks for some periods were missing. Using ratios calculated from financial statements is a matter of concern but they are still helpful in assessing the financial soundness of banks.

Finally, the study only provides a "snapshot" of assessment, opinion and insight at the time when it is conducted. The results of the study are not absolutely stable but they are relatively so due to the changing environment. Therefore, the assessment of the financial soundness of banks and of models for predicting financial unsoundness should be constantly revised.

### 6.5 Future Research

This study has highlighted some interesting possibilities for future research. Regarding the assessment of the financial soundness of the banking sector in Kazakhstan, the applied cluster based methodology could be developed by exploring the dependence of the financial soundness of banks on their activity priorities in the banking business.

Future research could use an integrated prediction model based on the MDA, Logit and Probit models with alternative variables to increase the prediction time horizon. Market based and macroeconomic indicators can serve as alternative variables.

Future research could also explore the predictability of the models in different economic conditions namely economic condition, before the crisis, during the crisis and after the crisis, so as to identify significant variables for each period.

Finally, future research could focus on the comparison of model performances between Kazakhstan and developed countries such as UK.

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## Appendix 2A: Harmonization of Capital Requirements of Basel III and the National Bank

| Component | Requirements of Basel taking into account changes (Basel III) | Requirements of National Bank | Harmonization |
|---|---|---|---|
| 1 | 2 | 3 | 4 |
| Common Equity (CE) | Paid up ordinary shares<br>+<br>retained earnings (reserves) | No | Introduction of common equity from 01.01.2015:<br>Paid up ordinary shares<br>+ reserves formed by net earnings of previous years to cover bank risks |
| Tier 1 Capital (C I) | Paid up ordinary shares +<br>retained net earnings (reserves))<br>+ non-cumulative preferred shares<br>+ retained income of previous years<br>+ supplementary capital corresponding to the criteria of Basel III<br>+ perpetual financial instruments (with the exception of C I for 10 years starting from 2013)<br>- goodwill and intangible assets;<br>- losses from previous years<br>- excess of expenditure over income of the current year | Ordinary shares excluding own repurchased shares<br>+ retained net earnings of previous years<br>+ preferred shares<br>+ additional capital<br>+ perpetual financial instruments +<br>deferred tax liability generated by net earnings<br>- intangible assets - losses from previous years<br>- losses of current year | Adjustment of CI:<br>• Excluded are the requirement to include preferred shares of no more than 15% of C I from 01.07.2011 and the rule providing for exclusion from C I calculation of perpetual financial instruments from 01.07.2011<br>• Exclusion of preferred shares from C I calculation from 01.01.2015 and of perpetual financial instruments from 01.01.2015 |
| Tier 2 Capital (C II) | Retained net earnings of current year<br>+ revaluation reserves<br>+ general reserves and provisions for losses<br>+ subordinated debt<br>+ cumulative preferred shares<br>+ hybrid capital instruments | Retained earnings of current year<br>+ size of revaluation of fixed assets and securities<br>+ size of reserves (provisions) for bank risks in an amount of not more than 1.25% of risk-weighted total assets risk minus non-invested balances taken under custody agreement | Adjustment of C II:<br>Inclusion in C II:<br>• general reserves including dynamic reserves in an amount of not more than 1.25<br>• % of weighted risk assets from 01.01.2015;<br>• the amount of preferred shares from 01.01.2015;<br>• perpetual financial instruments in full from 01.01.2015;<br>• subordinated tier 2 debt in full from 01.01.2015. |

Appendix 2A Continuation

| 1 | 2 | 3 | 4 |
|---|---|---|---|
| | | + subordinated debt of tier 2 bank included in CE in an amount of not more than 50% of the amount of CI, minus its own subordinated debt repurchased by the Bank<br>+ share (remainder) of preferred stock<br>+ perpetual financial instruments | |
| Tier 2 capital (C II) | Retained net earnings of current year<br>+ revaluation reserves<br>+ general reserves and provisions for losses<br>+ subordinated debt<br>+ cumulative preferred shares<br>+ hybrid capital instruments | Retained earnings of current year<br>+ size of revaluation of fixed assets and securities<br>+ size of reserves (provisions) for bank risks in an amount of not more than 1.25% of risk-weighted total assets risk minus non-invested balances taken under custody agreement<br>+ subordinated debt of tier 2 bank included in CE in an amount of not more than 50% of the amount of CI, minus its own subordinated debt repurchased by the Bank<br>+ share (remainder) of preferred stock<br>+ perpetual financial instruments | Adjustment of C II:<br>Inclusion in C II:<br>• general reserves including dynamic reserves in an amount of not more than 1.25 percent of weighted risk assets from 01.01.2015;<br>• the amount of preferred shares from 01.01.2015;<br>• perpetual financial instruments in full from 01.01.2015;<br>• subordinated tier 2 debt in full from 01.01.2015. |
| Limits | Withdraw CII ≤ CI | CII ≤ CI | Withdraw CII ≤ CI from 01.01.2015 |
| Tier 3 Capital (CIII) | Withdraw CIII | Subordinated tier 3 debt - short-term subordinated debt with original maturities from 2 to 5 years. Subordinated tier 2 debt not included in | Withdraw CIII from 01.01.2015 |

Appendix 2A Continuation

| 1 | 2 | 3 | 4 |
|---|---|---|---|
| | | CII, except its amortized part that can be included in CIII. | |
| Deductions from CE | Investment in the capital of subsidiary financial institutions and other organizations affiliated to the bank Investment in the capital of other financial organizations ≥ 10% of ordinary shares of financial organization | Investment in the capital of parent organization (01.01.2015) Investment in capital of subsidiary (from 01.01.2015) | Adjustment from 01.01.2015: Investment in the capital of other financial organizations ≥ 10% of ordinary shares of the financial organization |
| | Total investment in the capital of other financial organizations ≥ 10% of bank's common equity ≥ 10% to be deducted Investment in the capital of non-bank commercial organization ≥ 15% of common equity of bank from 20% in 2014 to 100% in 2019 Total investment in the capital of non-bank organizations – the amount of ≥ 60 % of common equity of bank to be deducted from 20% in 2014 to 100% in 2019 | Investment in capital, subordinated debt and equity investments in other entities, the aggregate amount of which exceeds 10% of the total amount of capital of tier 1 and tier 2 banks | Total investment in the capital of other financial organizations ≥ 10% of bank's common equity ≥ 10% to be deducted Total investment in the capital of non-commercial organizations – the amount of ≥ 60% per cent of bank's common equity to be deducted |
| | Deduction of investment is made by the principle of 50% from tier capital l and 50% from tier capital II | Investment of bank is within the share of tier 1 capital in the total amount of tier 1 capital and included in the calculation of equity capital of tier capital II | Investment of bank is within the share of tier capital I in the total amount of tier capital I and included in the calculation of equity capital of tier capital II |

**Source:** National Bank

## Appendix 2B: Harmonization of Capital Adequacy Standards under Basel III with National Bank Requirements

| | | Current requirements of NB taking into account the deferred measures | | | | Harmonization of NB requirements | Basel III | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Current[1] | 01.07.11 | 01.07.12 | 01.07.13 | from 2013 | 2013 | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
| Adequacy ratio of bank's CE (C1-1) | | 5%<br>6%<br>7% | ~~5%~~[2]<br>~~6%~~<br>~~7%~~ | ~~7%~~<br>~~8%~~<br>~~9%~~ | ~~8%~~<br>~~9%~~<br>~~10%~~ | 5% | | 2013-2016 Score | | | Introduction | | |
| Common equity | min | | | | | 4.5% | 3.5% | 4% | 4.5% | 4.5% | 4.5% | 4.5% | 4.5% |
| | min+CB | | | | | 7% | 3.5% | 4% | 4.5% | 5.125% | 5.75% | 6.375% | 7.0% |
| Tier capital I (C1-2) | min | 5%<br>6%<br>7% | ~~8%~~<br>~~9%~~<br>~~10%~~ | | | 6% | 4.5% | 5.5% | 6% | 6% | 6% | 6% | 6% |
| | min+CB | | | | | 8.5% | 4.5% | 5.5% | 6% | 6.625% | 7.25% | 7.875% | 8.5% |
| Equity capital (C2) | min | 10%<br>12%<br>14% | | | | 8% | 8% | 8% | 8% | 8% | 8% | 8% | 8% |
| | min+CB | | | | | 10.5% | 8% | 8% | 8% | 8.625% | 9.25% | 9.875% | 10.5% |
| Conservation buffer (CB) | | | | | | 2.5% | | | | 0.625% | 1.25% | 1.875% | 2.5% |
| Countercyclical buffer | | | | | | 0-2.5% | 0-2.5% (specified by the national legislation) | | | | | | |
| Systemic buffer (SB) | | | | | | C2 + 2% | C1 + 2% | | | | | | |

1 Respectively:
- for the banks having a bank holding
- for the banks having a large participant of individuals
- for the banks having no bank holding and a major participant of individuals

**Source:** National Bank

**Appendix 2C: Harmonization of Capital Adequacy Standards under Basel III with National Bank Requirements**

| | | Current requirements of NB, taking into account the deferred measures | Harmonization of NB requirements | Basel III | | | | |
|---|---|---|---|---|---|---|---|---|
| | | Current[1] | from 2013 | 2013 - 2015 | 2016 | 2017 | 2018 | 2019 |
| Equity capital adequacy ratio of the banking conglomerate (k) | Min | 10%<br>12%<br>14% | 8% | 8% | 8% | 8% | 8% | 8% |
| | min+CB | | 10.5% | 8% | 8.625% | 9.25% | 9.875% | 10.5% |
| Conservation buffer (CB) | 2.5% | | | | 0.625% | 1.25% | 1.875% | 2.5% |
| Systemic buffer (SB) | k + 2%[2] | | | C1+2% | | | | |

1 - Respectively:
- for the banks having a bank holding
- for the banks having a large participant of individuals
- for the banks having no bank holding and a major participant of individuals

2 Applied to:
- the bank having a significant share of assets, loans and deposits including individuals and in the banking system and a large concentration of financial resources by industry defined by FSB;
- and/or the bank which is a parent organization of the banking conglomerate

**Source:** National Bank

## Appendix 2D: Requirements for Weighting Assets according to the Credit Risk

| Assets | | from AAA to AA- | from A+ to A- | from BBB+ to BBB- | from BB+ to BB- | from B+ to B- | below B- | Un-rated | Note |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Requirements for the state and central banks | Basel | 0 | 20 | 50 | 100 | 100 | 150 | 100 | |
| | NB | 0 – for non-residents<br>0 - for the Government and NB | 20 – for non-residents | 50 - for non-residents | 100 - for non-residents | 100 - for non-residents | 100 - for non-residents | Deduction from EC | - allowed transactions with bonds of foreign states with rating not less than “BBB-“ (RLA No.128) |
| Requirements for state enterprises and organizations not related to the Central Government and to local authorities | Basel | 20 | 50 | 100 | 100 | 100 | 150 | 100 | |
| | NB | 20 including local authorities;<br>0 - FSB “Samruk-Kazyna” | 50 – for non-residents | 100- for non-residents | 100- for non-residents | 150 - for non-residents | 150 - for non-residents | Deduction from CE | - allowed transactions with bonds of foreign issuers with rating of not less than “BBB-“ and of RK issuers not less than “BB-“ |
| Requirements for international financial organizations | Basel | 0 / 20 | 50 | 50 | 100 | 100 | 150 | 50 | |
| | NB | 0 | 20 | 50 | 100 | 100 | 150 | Deduction from CE | - allowed transactions with bonds of foreign states with rating not less than “BBB-“ |
| Requirements for financial companies. banks and corporations | | from AAA to AA- | from A+ to A- | from BBB+ to BB- | below BB- | | No rating | | |
| | Basel | 20 | 50 | 100 | 150 | | 100 | | |
| | NB | 20 | 50 | 100 | 150 for non-residents<br>100 for residents | | 150 for non-residents<br>100 for non-residents | | |
| | | | | | | | | | |
| Securitisation positions | | from AAA to AA- | from A+ to A- | from BBB+ to BBB- | from BB+ to BB- | | below BB- and unrated | | |
| | Basel | 20 | 50 | 100 | 350 | | Deduction from EC | | |
| | NB | 20 | 50 | 100 | 350 | | Deduction from EC | | |

Appendix 2D Continuation

| Other requirements | | Loans to individuals | | Secured by residential real estate (mortgage housing loans) | | Secured by commercial real estate | |
|---|---|---|---|---|---|---|---|
| | Basel | | 75 | | 35 | 100 | |
| | NB | | 100 | 50 (loan/mortgage ≤ 51%)<br>75 (loan/mortgage from 51% to 60%)<br>100 | | 100 | |

**Source:** National Bank

**Appedix 3A: Data for Cluster and PCA Analysis**

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Al Hilal Islamic Bank | 2014 | 0.640 | 0.617 | 0.999 | 1.779 | 0.562 | 0.000 | 0.000 | 0.035 | 0.023 | 0.037 | 0.013 | 0.048 | 0.050 | 0.147 | 2.588 |
| 2 | Alliance Bank* | 2014 | 0.103 | 0.075 | 0.109 | 0.115 | 8.685 | 0.498 | 29.001 | 0.012 | 0.005 | 0.047 | 0.116 | 0.022 | -0.006 | 0.255 | 1.104 |
| 3 | AsiaCredit Bank | 2014 | 0.209 | 0.191 | 0.199 | 0.264 | 3.791 | 0.037 | 0.116 | 0.018 | 0.020 | 0.094 | 0.094 | 0.062 | 0.052 | -1.092 | 0.420 |
| 4 | ATF Bank | 2014 | 0.098 | 0.092 | 0.122 | 0.109 | 9.161 | 0.423 | 4.343 | 0.007 | 0.000 | 0.003 | 0.045 | 0.023 | 0.010 | 0.025 | 1.163 |
| 5 | Bank Astana-Finance | 2014 | 0.152 | 0.144 | 0.221 | 0.179 | 5.599 | 0.068 | 0.262 | 0.002 | 0.004 | 0.025 | 0.040 | 0.060 | 0.053 | -0.875 | 0.583 |
| 6 | Bank Centercredit | 2014 | 0.132 | 0.085 | 0.092 | 0.152 | 6.568 | 0.163 | 1.709 | 0.008 | 0.002 | 0.013 | 0.046 | 0.050 | 0.037 | -0.328 | 0.456 |
| 7 | Bank Kassa Nova | 2014 | 0.190 | 0.122 | 0.166 | 0.234 | 4.276 | 0.009 | 0.047 | 0.022 | 0.014 | 0.075 | 0.073 | 0.075 | 0.068 | -0.339 | 4.485 |
| 8 | Bank Positive Kazakhstan | 2014 | 0.506 | 0.493 | 0.407 | 1.025 | 0.976 | 0.055 | 0.081 | 0.028 | 0.010 | 0.020 | 0.022 | 0.067 | 0.054 | 0.148 | 0.524 |
| 9 | Bank RBK | 2014 | 0.096 | 0.066 | 0.087 | 0.106 | 9.455 | 0.031 | 0.276 | 0.015 | 0.007 | 0.075 | 0.093 | 0.057 | 0.052 | 0.265 | 0.851 |
| 10 | BTA Bank* | 2014 | 0.156 | 0.141 | 0.250 | 0.185 | 5.394 | 0.849 | 8.513 | 0.007 | 0.018 | 0.114 | 0.079 | 0.057 | -0.020 | -0.197 | 1.448 |
| 11 | Citibank of Kazakhstan | 2014 | 0.155 | 0.149 | 0.206 | 0.184 | 5.435 | 0.000 | 0.000 | 0.003 | 0.026 | 0.167 | 0.050 | 0.014 | 0.012 | 0.121 | 0.955 |
| 12 | Delta Bank | 2014 | 0.117 | 0.095 | 0.128 | 0.132 | 7.550 | 0.008 | 0.059 | 0.006 | 0.019 | 0.162 | 0.093 | 0.079 | 0.059 | 0.108 | 2.062 |
| 13 | Eurasian Bank | 2014 | 0.134 | 0.072 | 0.086 | 0.154 | 6.491 | 0.089 | 0.675 | 0.025 | 0.022 | 0.162 | 0.095 | 0.083 | 0.071 | -0.252 | 1.005 |
| 14 | Eximbank Kazakhstan | 2014 | 0.261 | 0.248 | 0.213 | 0.353 | 2.835 | 0.019 | 0.060 | 0.011 | 0.004 | 0.015 | 0.050 | 0.080 | 0.056 | -0.179 | 0.409 |
| 15 | ForteBank | 2014 | 0.312 | 0.214 | 0.363 | 0.453 | 2.210 | 0.059 | 0.152 | 0.000 | 0.022 | 0.069 | 0.032 | 0.041 | 0.036 | 0.281 | 0.978 |
| 16 | Halyk Bank of Kazakhstan | 2014 | 0.153 | 0.095 | 0.112 | 0.180 | 5.548 | 0.163 | 0.776 | 0.008 | 0.035 | 0.228 | 0.056 | 0.058 | 0.044 | -0.041 | 0.734 |
| 17 | Kaspi Bank | 2014 | 0.120 | 0.059 | 0.073 | 0.136 | 7.340 | 0.122 | 1.041 | 0.020 | 0.038 | 0.319 | 0.114 | 0.087 | 0.064 | -0.232 | 2.266 |
| 18 | Kazinvestbank | 2014 | 0.123 | 0.087 | 0.100 | 0.140 | 7.124 | 0.139 | 0.963 | 0.014 | 0.002 | 0.016 | 0.070 | 0.042 | 0.033 | -0.205 | 0.541 |
| 19 | Kazkommertsbank | 2014 | 0.179 | 0.122 | 0.126 | 0.218 | 4.596 | 0.294 | 1.982 | 0.005 | 0.018 | 0.102 | 0.070 | 0.069 | 0.034 | -0.346 | 0.522 |
| 20 | Nurbank | 2014 | 0.173 | 0.151 | 0.184 | 0.209 | 4.787 | 0.293 | 1.327 | 0.013 | -0.131 | -0.759 | -0.079 | 0.027 | 0.006 | -0.296 | 1.017 |
| 21 | Qazaq Banki | 2014 | 0.110 | 0.107 | 0.177 | 0.124 | 8.084 | 0.000 | 0.001 | 0.020 | 0.007 | 0.065 | 0.109 | 0.048 | 0.040 | -0.140 | 0.605 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 22 | Shinhan Bank of Kazakhstan | 2014 | 0.641 | 0.615 | 1.190 | 1.789 | 0.559 | 0.000 | 0.000 | 0.018 | 0.024 | 0.038 | 0.030 | 0.052 | 0.045 | -0.041 | 1.509 |
| 23 | Temirbank* | 2014 | 0.143 | 0.076 | 0.090 | 0.166 | 6.007 | 0.402 | 10.681 | 0.016 | 0.001 | 0.005 | 0.060 | 0.054 | 0.020 | -0.138 | 1.698 |
| 24 | TPBK | 2014 | 0.240 | 0.229 | 0.379 | 0.316 | 3.168 | 0.000 | 0.000 | 0.004 | 0.010 | 0.043 | 0.013 | 0.020 | 0.018 | 0.050 | 0.755 |
| 25 | Tsesnabank | 2014 | 0.101 | 0.061 | 0.066 | 0.113 | 8.875 | 0.037 | 0.342 | 0.010 | 0.018 | 0.175 | 0.082 | 0.055 | 0.051 | 0.075 | 0.731 |
| 26 | Zaman-Bank | 2014 | 0.761 | 0.748 | 0.896 | 3.189 | 0.314 | 0.058 | 0.057 | 0.010 | 0.013 | 0.017 | 0.023 | 0.064 | 0.027 | 0.746 | 2.945 |
| 27 | SB Alpha-Bank | 2014 | 0.162 | 0.101 | 0.098 | 0.193 | 5.181 | 0.011 | 0.056 | 0.016 | 0.027 | 0.168 | 0.086 | 0.056 | 0.047 | 0.924 | 0.758 |
| 28 | SB Bank of China in Kazakhstan | 2014 | 0.159 | 0.141 | 0.555 | 0.189 | 5.281 | 0.000 | 0.000 | 0.004 | 0.018 | 0.113 | 0.024 | 0.015 | 0.015 | 0.112 | 1.049 |
| 29 | SB Home Credit and Finance Bank | 2014 | 0.240 | 0.131 | 0.162 | 0.316 | 3.163 | 0.021 | 0.146 | 0.042 | 0.105 | 0.437 | 0.076 | 0.269 | 0.214 | 0.024 | 3.833 |
| 30 | SB HSBC Bank Kazakhstan | 2014 | 0.137 | 0.119 | 0.197 | 0.159 | 6.286 | 0.065 | 0.198 | 0.014 | 0.022 | 0.158 | 0.047 | 0.036 | 0.035 | -0.147 | 0.977 |
| 31 | SB KZI Bank | 2014 | 0.672 | 0.620 | 0.718 | 2.050 | 0.488 | 0.035 | 0.034 | 0.016 | 0.045 | 0.067 | 0.065 | 0.077 | 0.073 | -0.170 | 1.002 |
| 32 | SB NB of Pakistan in Kazakhstan | 2014 | 0.823 | 0.775 | 0.835 | 4.636 | 0.216 | 0.184 | 0.193 | 0.038 | 0.046 | 0.056 | 0.057 | 0.108 | 0.058 | 0.168 | 2.830 |
| 33 | SB PNB – Kazakhstan | 2014 | 0.836 | 0.816 | 1.097 | 5.088 | 0.197 | 0.157 | 0.100 | 0.023 | 0.001 | 0.001 | 0.003 | 0.057 | 0.018 | 0.636 | 7.326 |
| 34 | SB RBS (Kazakhstan) | 2014 | 0.326 | 0.295 | 0.460 | 0.483 | 2.069 | 0.000 | 0.000 | 0.011 | 0.025 | 0.075 | 0.037 | 0.017 | 0.016 | 0.314 | 1.483 |
| 35 | SB Sberbank | 2014 | 0.128 | 0.080 | 0.079 | 0.146 | 6.842 | 0.074 | 0.283 | 0.008 | 0.021 | 0.163 | 0.154 | 0.054 | 0.048 | -0.325 | 0.848 |
| 36 | SB Taib Kazakh Bank | 2014 | 0.474 | 0.455 | 0.576 | 0.903 | 1.108 | 0.032 | 0.038 | 0.018 | 0.013 | 0.028 | 0.002 | 0.057 | 0.049 | -1.790 | 1.520 |
| 37 | SB VTB Bank (Kazakhstan) | 2014 | 0.123 | 0.113 | 0.122 | 0.140 | 7.136 | 0.031 | 0.195 | 0.030 | 0.004 | 0.033 | 0.052 | 0.067 | 0.059 | -0.128 | 0.948 |
| | | | | | | | | | | | | | | | | | |
| 1 | Al Hilal Islamic Bank | 2013 | 0.871 | 0.834 | 0.718 | 6.757 | 0.148 | 0.000 | 0.000 | 0.037 | 0.025 | 0.029 | 0.032 | 0.066 | 0.069 | 0.133 | 1.919 |
| 2 | Alliance Bank* | 2013 | 0.152 | 0.091 | 0.120 | 0.179 | 5.589 | 0.340 | 2.221 | 0.014 | 0.013 | 0.210 | 0.090 | 0.038 | 0.002 | -0.005 | 1.148 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 3 | AsiaCredit Bank | 2013 | 0.191 | 0.188 | 0.228 | 0.237 | 4.228 | 0.045 | 0.155 | 0.016 | 0.000 | 0.001 | 0.072 | 0.069 | 0.057 | -0.808 | 0.810 |
| 4 | ATF Bank | 2013 | 0.133 | 0.099 | 0.108 | 0.153 | 6.518 | 0.362 | 2.460 | 0.007 | -0.013 | -0.154 | 0.038 | 0.029 | 0.018 | -0.485 | 0.823 |
| 5 | Bank Astana-Finance | 2013 | 0.113 | 0.097 | 0.140 | 0.127 | 7.863 | 0.068 | 0.353 | 0.033 | 0.023 | 0.185 | 0.043 | 0.076 | 0.068 | -0.646 | 0.686 |
| 6 | Bank Centercredit | 2013 | 0.129 | 0.086 | 0.091 | 0.149 | 6.735 | 0.098 | 0.607 | 0.009 | 0.000 | 0.005 | 0.048 | 0.019 | 0.011 | -0.669 | 0.623 |
| 7 | Bank Kassa Nova | 2013 | 0.338 | 0.231 | 0.242 | 0.510 | 1.962 | 0.007 | 0.016 | 0.022 | -0.001 | -0.003 | 0.078 | 0.098 | 0.087 | 0.301 | 0.758 |
| 8 | Bank Positive Kazakhstan | 2013 | 0.633 | 0.653 | 0.646 | 1.723 | .581 | 0.111 | 0.126 | 0.036 | 0.007 | 0.011 | 0.018 | 0.062 | 0.052 | -0.248 | 0.942 |
| 9 | Bank RBK | 2013 | 0.172 | 0.166 | 0.173 | 0.208 | 4.820 | 0.024 | 0.102 | 0.016 | 0.003 | 0.018 | 0.092 | 0.066 | 0.061 | -0.228 | 0.711 |
| 10 | BTA Bank* | 2013 | 0.143 | 0.140 | 0.232 | 0.167 | 5.977 | 0.850 | 8.047 | 0.008 | -0.230 | -1.664 | -0.170 | -0.010 | -0.020 | -0.602 | 0.751 |
| 11 | Citibank of Kazakhstan | 2013 | 0.127 | 0.118 | 0.158 | 0.145 | 6.899 | 0.011 | 0.045 | 0.003 | 0.022 | 0.165 | 0.040 | 0.018 | 0.018 | 0.181 | 0.743 |
| 12 | Delta Bank | 2013 | 0.129 | 0.118 | 0.187 | 0.149 | 6.731 | 0.004 | 0.025 | 0.006 | 0.011 | 0.085 | 0.088 | 0.098 | 0.076 | 0.044 | 1.468 |
| 13 | Eurasian Bank | 2013 | 0.120 | 0.075 | 0.080 | 0.137 | 7.301 | 0.057 | 0.373 | 0.024 | 0.021 | 0.207 | 0.093 | 0.070 | 0.060 | 0.021 | 0.852 |
| 14 | Eximbank Kazakhstan | 2013 | 0.183 | 0.169 | 0.162 | 0.224 | 4.456 | 0.075 | 0.312 | 0.010 | 0.007 | 0.040 | 0.047 | 0.069 | 0.050 | 0.029 | 0.442 |
| 15 | ForteBank | 2013 | 0.239 | 0.158 | 0.349 | 0.314 | 3.189 | 0.086 | 0.166 | 0.040 | 0.019 | 0.098 | 0.032 | 0.042 | 0.034 | 0.281 | 1.143 |
| 16 | Halyk Bank of Kazakhstan | 2013 | 0.123 | 0.084 | 0.102 | 0.141 | 7.102 | 0.149 | 0.789 | 0.008 | 0.025 | 0.192 | 0.065 | 0.041 | 0.030 | -0.018 | 0.744 |
| 17 | Kaspi Bank | 2013 | 0.147 | 0.079 | 0.084 | 0.173 | 5.788 | 0.065 | 0.365 | 0.018 | 0.032 | 0.283 | 0.125 | 0.082 | 0.057 | -0.892 | 1.641 |
| 18 | Kazinvestbank | 2013 | 0.096 | 0.070 | 0.096 | 0.107 | 9.370 | 0.128 | 0.854 | 0.012 | -0.014 | -0.154 | 0.023 | 0.034 | 0.026 | 0.127 | 0.599 |
| 19 | Kazkommertsbank | 2013 | 0.153 | 0.126 | 0.122 | 0.180 | 5.543 | 0.179 | 1.102 | 0.005 | 0.001 | 0.003 | 0.047 | 0.062 | 0.032 | 0.225 | 0.503 |
| 20 | Nurbank | 2013 | 0.170 | 0.177 | 0.205 | 0.205 | 4.883 | 0.370 | 1.632 | 0.013 | -0.021 | -0.073 | 0.025 | 0.025 | 0.004 | -0.077 | 0.754 |
| 21 | Qazaq Banki | 2013 | 0.474 | 0.478 | 0.575 | 0.900 | 1.111 | 0.001 | 0.001 | 0.024 | 0.004 | 0.009 | 0.020 | 0.052 | 0.029 | -2.396 | 2.151 |
| 22 | Shinhan Bank of Kazakhstan | 2013 | 0.648 | 0.634 | 10.200 | 1.844 | 0.542 | 0.000 | 0.000 | 0.018 | 0.023 | 0.035 | 0.030 | 0.053 | 0.043 | -0.051 | 1.229 |
| 23 | Temirbank* | 2013 | 0.122 | 0.070 | 0.084 | 0.139 | 7.176 | 0.446 | 30.071 | 0.017 | 0.050 | 0.204 | 0.109 | 0.057 | 0.016 | 0.241 | 1.418 |
| 24 | TPBK | 2013 | 0.335 | 0.323 | 10.882 | 0.503 | 1.987 | 0.000 | 0.000 | 0.005 | 0.012 | 0.035 | 0.017 | 0.014 | 0.012 | 0.240 | 1.827 |
| 25 | Tsesnabank | 2013 | 0.114 | 0.064 | 0.067 | 0.128 | 7.806 | 0.022 | 0.148 | 0.012 | 0.017 | 0.213 | 0.090 | 0.059 | 0.056 | -0.962 | 0.485 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 26 | Zaman-Bank | 2013 | 0.525 | 0.520 | 10.000 | 1.105 | 0.905 | 0.029 | 0.036 | 0.007 | 0.009 | 0.017 | 0.026 | 0.039 | 0.018 | 0.073 | 1.410 |
| 27 | SB Alpha-Bank | 2013 | 0.173 | 0.114 | 0.119 | 0.210 | 4.773 | 0.022 | 0.082 | 0.013 | 0.017 | 0.117 | 0.063 | 0.050 | 0.042 | 0.011 | 0.518 |
| 28 | SB Bank of China in Kazakhstan | 2013 | 0.226 | 0.200 | 0.347 | 0.291 | 3.434 | 0.000 | 0.000 | 0.005 | 0.026 | 0.113 | 0.035 | 0.009 | 0.009 | 0.179 | 1.051 |
| 29 | SB Home Credit and Finance Bank | 2013 | 0.282 | 0.153 | 0.140 | 0.394 | 2.541 | 0.054 | 0.164 | 0.027 | 0.121 | 0.434 | 0.184 | 0.262 | 0.221 | 0.423 | 2.266 |
| 30 | SB HSBC Bank Kazakhstan | 2013 | 0.125 | 0.110 | 0.168 | 0.143 | 6.986 | 0.071 | 0.214 | 0.016 | 0.026 | 0.200 | 0.036 | 0.037 | 0.035 | 0.163 | 0.997 |
| 31 | SB KZI Bank | 2013 | 0.742 | 0.712 | 10.131 | 2.878 | 0.348 | 0.065 | 0.055 | 0.020 | 0.029 | 0.038 | 0.040 | 0.057 | 0.055 | 0.239 | 2.247 |
| 32 | SB NB of Pakistan in Kazakhstan | 2013 | 0.803 | 0.784 | 0.855 | 4.071 | 0.246 | 0.007 | 0.007 | 0.031 | 0.024 | 0.029 | 0.044 | 0.096 | 0.051 | 0.014 | 2.658 |
| 33 | SB PNB – Kazakhstan | 2013 | 0.840 | 0.884 | 10.200 | 5.240 | 0.191 | 0.183 | 0.101 | 0.018 | -0.080 | -0.089 | -0.077 | 0.041 | 0.004 | 0.135 | 7.600 |
| 34 | SB RBS (Kazakhstan) | 2013 | 0.191 | 0.175 | 0.231 | 0.236 | 4.241 | 0.036 | 0.078 | 0.012 | 0.016 | 0.081 | 0.022 | 0.009 | 0.008 | 0.045 | 0.934 |
| 35 | SB Sberbank | 2013 | 0.137 | 0.087 | 0.091 | 0.159 | 6.294 | 0.051 | 0.270 | 0.013 | 0.019 | 0.153 | 0.070 | 0.054 | 0.049 | 0.397 | 0.920 |
| 36 | SB Taib Kazakh Bank | 2013 | 0.821 | 0.573 | 0.596 | 4.588 | 0.218 | 0.246 | 0.093 | 0.023 | -0.037 | -0.060 | -0.024 | 0.035 | 0.007 | -1.292 | 4.404 |
| 37 | SB VTB Bank (Kazakhstan) | 2013 | 0.170 | 0.172 | 0.172 | 0.206 | 4.865 | 0.026 | 0.129 | 0.033 | -0.011 | -0.061 | 0.043 | 0.069 | 0.059 | 0.290 | 0.916 |
| | | | | | | | | | | | | | | | | | |
| 1 | Al Hilal Islamic Bank | 2012 | 0.916 | 0.921 | 1.518 | 10.845 | 0.092 | 0.000 | 0.000 | 0.037 | -0.011 | -0.012 | -0.007 | 0.021 | 0.021 | 0.041 | 14.217 |
| 2 | Alliance Bank* | 2012 | 0.126 | 0.078 | 0.093 | 0.144 | 6.938 | 0.377 | 3.022 | 0.015 | 0.021 | 1.233 | 0.096 | 0.030 | -0.010 | 0.120 | 1.580 |
| 3 | AsiaCredit Bank | 2012 | 0.401 | 0.375 | 0.425 | 0.669 | 1.495 | 0.035 | 0.056 | 0.021 | -0.015 | -0.036 | 0.034 | 0.086 | 0.072 | -1.328 | 1.521 |
| 4 | ATF Bank | 2012 | 0.116 | 0.080 | 0.089 | 0.132 | 7.594 | 0.243 | 1.836 | 0.006 | -0.038 | -0.588 | 0.004 | 0.031 | 0.022 | -0.415 | 1.103 |
| 5 | Bank Astana-Finance | 2012 | 0.105 | 0.101 | 0.171 | 0.117 | 8.552 | 0.050 | 0.240 | 0.014 | 0.002 | 0.018 | 0.022 | 0.064 | 0.050 | -0.393 | 0.837 |
| 6 | Bank Centercredit | 2012 | 0.128 | 0.083 | 0.094 | 0.147 | 6.787 | 0.089 | 0.524 | 0.007 | 0.003 | 0.038 | 0.053 | 0.023 | 0.016 | -0.679 | 0.796 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | Bank Kassa Nova | 2012 | 0.798 | 0.546 | 0.575 | 3.954 | 0.253 | 0.002 | 0.002 | 0.047 | 0.003 | 0.006 | 0.080 | 0.139 | 0.111 | 0.335 | 4.247 |
| 8 | Bank Positive Kazakhstan | 2012 | 0.594 | 0.614 | 0.831 | 1.464 | 0.683 | 0.144 | 0.125 | 0.033 | -0.007 | -0.010 | 0.000 | 0.037 | 0.028 | -0.063 | 1.659 |
| 9 | Bank RBK | 2012 | 0.141 | 0.133 | 0.177 | 0.164 | 6.111 | 0.002 | 0.008 | 0.014 | 0.001 | 0.004 | 0.062 | 0.061 | 0.054 | 0.017 | 1.628 |
| 10 | BTA Bank* | 2012 | 0.187 | 0.115 | 0.118 | 0.231 | 4.338 | 0.484 | 3.342 | 0.007 | -0.015 | 0.097 | 0.072 | -0.010 | -0.037 | -0.589 | 1.465 |
| 11 | Citibank of Kazakhstan | 2012 | 0.065 | 0.069 | 0.125 | 0.070 | 14.287 | 0.019 | 0.073 | 0.001 | 0.010 | 0.143 | 0.018 | 0.011 | 0.011 | -0.031 | 0.879 |
| 12 | Delta Bank | 2012 | 0.178 | 0.168 | 0.185 | 0.216 | 4.631 | 0.007 | 0.033 | 0.007 | 0.005 | 0.031 | 0.063 | 0.083 | 0.068 | 0.020 | 1.323 |
| 13 | Eurasian Bank | 2012 | 0.109 | 0.062 | 0.066 | 0.123 | 8.141 | 0.070 | 0.467 | 0.016 | 0.018 | 0.201 | 0.089 | 0.060 | 0.052 | -0.028 | 1.154 |
| 14 | Eximbank Kazakhstan | 2012 | 0.157 | 0.147 | 0.156 | 0.186 | 5.375 | 0.053 | 0.262 | 0.007 | 0.004 | 0.023 | 0.046 | 0.060 | 0.042 | -0.463 | 0.556 |
| 15 | ForteBank | 2012 | 0.297 | 0.218 | 0.459 | 0.423 | 2.363 | 0.172 | 0.212 | 0.030 | -0.029 | -0.117 | -0.016 | 0.048 | 0.035 | 0.314 | 1.084 |
| 16 | Halyk Bank of Kazakhstan | 2012 | 0.125 | 0.092 | 0.119 | 0.142 | 7.028 | 0.150 | 0.744 | 0.006 | 0.016 | 0.126 | 0.055 | 0.045 | 0.032 | -0.077 | 0.895 |
| 17 | Kaspi Bank | 2012 | 0.153 | 0.081 | 0.088 | 0.181 | 5.533 | 0.065 | 0.363 | 0.015 | 0.028 | 0.256 | 0.119 | 0.099 | 0.075 | -0.887 | 1.513 |
| 18 | Kazinvestbank | 2012 | 0.134 | 0.098 | 0.107 | 0.155 | 6.449 | 0.100 | 0.573 | 0.013 | 0.001 | 0.008 | 0.048 | 0.036 | 0.024 | 0.465 | 0.726 |
| 19 | Kazkommertsbank | 2012 | 0.162 | 0.131 | 0.123 | 0.193 | 5.169 | 0.145 | 0.827 | 0.004 | 0.000 | 0.003 | 0.055 | 0.055 | 0.025 | 0.255 | 0.636 |
| 20 | Nurbank | 2012 | 0.178 | 0.174 | 0.192 | 0.217 | 4.603 | 0.323 | 1.505 | 0.011 | -0.004 | -0.016 | 0.040 | 0.034 | 0.006 | -0.104 | 0.835 |
| 21 | Qazaq Banki | 2012 | 0.395 | 0.397 | 0.504 | 0.654 | 1.529 | 0.002 | 0.002 | 0.035 | 0.002 | 0.005 | 0.023 | 0.054 | 0.032 | -0.582 | 4.733 |
| 22 | Shinhan Bank of Kazakhstan | 2012 | 0.590 | 0.575 | 0.886 | 1.442 | 0.694 | 0.000 | 0.000 | 0.013 | 0.016 | 0.026 | 0.022 | 0.050 | 0.040 | -0.081 | 1.284 |
| 23 | Temirbank* | 2012 | 0.114 | 0.078 | 0.095 | 0.129 | 7.764 | 0.471 | 3.586 | 0.015 | 0.002 | 0.008 | 0.068 | 0.039 | -0.005 | 0.329 | 2.439 |
| 24 | TPBK | 2012 | 0.360 | 0.347 | 30.597 | 0.562 | 1.778 | 0.000 | 0.000 | 0.003 | 0.012 | 0.035 | 0.017 | 0.014 | 0.013 | 0.194 | 1.495 |
| 25 | Tsesnabank | 2012 | 0.105 | 0.070 | 0.078 | 0.118 | 8.504 | 0.018 | 0.132 | 0.010 | 0.009 | 0.120 | 0.081 | 0.048 | 0.045 | -1.014 | 0.538 |
| 26 | Zaman-Bank | 2012 | 0.876 | 0.850 | 0.688 | 7.058 | 0.142 | 0.067 | 0.073 | 0.017 | 0.014 | 0.016 | 0.118 | 0.111 | 0.103 | 0.419 | 1.793 |
| 27 | SB Alpha-Bank | 2012 | 0.157 | 0.092 | 0.111 | 0.186 | 5.379 | 0.033 | 0.102 | 0.013 | 0.010 | 0.084 | 0.048 | 0.041 | 0.036 | -0.068 | 0.730 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 28 | SB Bank of China in Kazakhstan | 2012 | 0.221 | 0.195 | 0.656 | 0.284 | 3.519 | 0.010 | 0.003 | 0.003 | 0.026 | 0.117 | 0.033 | 0.010 | 0.009 | 0.173 | 1.165 |
| 29 | SB Home Credit and Finance Bank | 2012 | 0.279 | 0.139 | 0.145 | 0.386 | 2.591 | 0.030 | 0.080 | 0.034 | 0.132 | 0.477 | 0.185 | 0.396 | 0.353 | 0.000 | 1.963 |
| 30 | SB HSBC Bank Kazakhstan | 2012 | 0.106 | 0.090 | 0.104 | 0.119 | 8.431 | 0.058 | 0.301 | 0.013 | 0.023 | 0.197 | 0.036 | 0.049 | 0.047 | 0.111 | 0.611 |
| 31 | SB KZI Bank | 2012 | 0.664 | 0.644 | 1.479 | 1.973 | 0.507 | 0.186 | 0.071 | 0.018 | 0.018 | 0.026 | 0.028 | 0.052 | 0.048 | 0.245 | 2.323 |
| 32 | SB NB of Pakistan in Kazakhstan | 2012 | 0.870 | 0.864 | 1.205 | 6.699 | 0.149 | 0.015 | 0.009 | 0.027 | 0.010 | 0.011 | 0.025 | 0.092 | 0.059 | -0.016 | 6.131 |
| 33 | SB PNB – Kazakhstan | 2012 | 0.826 | 0.812 | 2.083 | 4.762 | 0.210 | 0.067 | 0.008 | 0.008 | -0.020 | -0.024 | -0.016 | 0.017 | -0.013 | 0.281 | 4.198 |
| 34 | SB RBS (Kazakhstan) | 2012 | 0.141 | 0.139 | 0.425 | 0.164 | 6.084 | 0.119 | 0.109 | 0.007 | -0.002 | -0.016 | 0.003 | 0.010 | 0.010 | -0.170 | 0.970 |
| 35 | SB Sberbank | 2012 | 0.117 | 0.080 | 0.085 | 0.132 | 7.573 | 0.053 | 0.331 | 0.013 | 0.016 | 0.154 | 0.073 | 0.058 | 0.052 | 0.006 | 0.438 |
| 36 | SB Taib Kazakh Bank | 2012 | 0.860 | 0.569 | 0.777 | 6.141 | 0.163 | 0.133 | 0.029 | 0.012 | -0.016 | -0.025 | 0.001 | 0.019 | -0.008 | 0.165 | 4.267 |
| 37 | SB VTB Bank (Kazakhstan) | 2012 | 0.281 | 0.281 | 0.308 | 0.391 | 2.556 | 0.001 | 0.002 | 0.036 | -0.029 | -0.104 | 0.022 | 0.052 | 0.036 | 0.464 | 1.749 |
| | | | | | | | | | | | | | | | | | |
| 1 | Al Hilal Islamic Bank | 2011 | 0.929 | 0.999 | 4.528 | 13.039 | .077 | 0.000 | 0.000 | 0.049 | -0.070 | -0.075 | -0.075 | 0.005 | -0.014 | 0.873 | 41.588 |
| 2 | Alliance Bank* | 2011 | 0.114 | 0.089 | 0.109 | 0.122 | 8.187 | 0.508 | 4.980 | 0.015 | 0.651 | 5.730 | 0.689 | 0.016 | -0.006 | 0.096 | 1.681 |
| 3 | AsiaCredit Bank | 2011 | 0.400 | 0.346 | 0.635 | 0.665 | 1.503 | 0.028 | 0.026 | 0.021 | 0.006 | 0.014 | 0.019 | 0.076 | 0.063 | -0.865 | 1.124 |
| 4 | ATF Bank | 2011 | 0.119 | 0.077 | 0.089 | 0.127 | 7.872 | 0.121 | 0.878 | 0.006 | -0.038 | -0.323 | 0.008 | 0.026 | 0.023 | -0.459 | 0.790 |
| 5 | Bank Astana-Finance | 2011 | 0.314 | 0.312 | 0.285 | 0.460 | 2.175 | 0.135 | 0.343 | 0.043 | -0.109 | -0.346 | -0.064 | 0.068 | 0.054 | -0.593 | 0.808 |
| 6 | Bank Centercredit | 2011 | 0.111 | 0.073 | 0.106 | 0.118 | 8.439 | 0.087 | 0.465 | 0.007 | -0.024 | -0.218 | 0.026 | 0.011 | 0.011 | -0.552 | 1.469 |
| 7 | Bank Kassa Nova | 2011 | 0.673 | 0.673 | 0.764 | 2.091 | 0.478 | 0.000 | 0.000 | 0.052 | -0.025 | -0.038 | -0.002 | 0.119 | 0.104 | 0.142 | 0.712 |
| 8 | Bank Positive Kazakhstan | 2011 | 0.361 | 0.346 | 0.939 | 0.552 | 1.811 | 0.448 | 0.275 | 0.022 | -0.013 | -0.036 | -0.008 | 0.039 | 0.032 | 0.042 | 2.113 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 9 | Bank RBK | 2011 | 0.644 | 0.589 | 0.689 | 1.813 | 0.552 | 0.002 | 0.002 | 0.014 | 0.009 | 0.013 | 0.010 | 0.119 | 0.008 | -1.855 | 1.853 |
| 10 | BTA Bank* | 2011 | 0.174 | 0.138 | 0.150 | 0.192 | 5.210 | 0.423 | 2.001 | 0.007 | 0.577 | 3.306 | 0.733 | -0.044 | -0.034 | -0.572 | 1.437 |
| 11 | Citibank of Kazakhstan | 2011 | 0.099 | 0.089 | 0.216 | 0.109 | 9.133 | 0.114 | 0.199 | 0.001 | 0.014 | 0.140 | 0.018 | 0.013 | 0.013 | -0.106 | 0.759 |
| 12 | Delta Bank | 2011 | 0.234 | 0.218 | 0.239 | 0.302 | 3.310 | 0.002 | 0.008 | 0.007 | 0.003 | 0.011 | 0.065 | 0.093 | 0.034 | 0.119 | 0.735 |
| 13 | Eurasian Bank | 2011 | 0.107 | 0.071 | 0.094 | 0.115 | 8.701 | 0.065 | 0.387 | 0.016 | 0.002 | 0.017 | 0.061 | 0.024 | 0.025 | -0.023 | 1.402 |
| 14 | Eximbank Kazakhstan | 2011 | 0.157 | 0.148 | 0.176 | 0.187 | 5.362 | 0.011 | 0.058 | 0.007 | 0.003 | 0.017 | 0.058 | 0.066 | 0.053 | -0.478 | 0.441 |
| 15 | ForteBank | 2011 | 0.344 | 0.339 | 0.727 | 0.528 | 1.894 | 0.166 | 0.196 | 0.037 | -0.103 | -0.299 | -0.057 | 0.046 | 0.019 | 0.306 | 1.519 |
| 16 | Halyk Bank of Kazakhstan | 2011 | 0.147 | 0.109 | 0.135 | 0.169 | 5.920 | 0.126 | 0.519 | 0.006 | 0.014 | 0.092 | 0.057 | 0.052 | 0.039 | -0.068 | 1.101 |
| 17 | Kaspi Bank | 2011 | 0.143 | 0.085 | 0.094 | 0.159 | 6.296 | 0.088 | 0.504 | 0.015 | 0.012 | 0.084 | 0.098 | 0.089 | 0.071 | -0.800 | 1.051 |
| 18 | Kazinvestbank | 2011 | 0.188 | 0.147 | 0.162 | 0.224 | 4.463 | 0.051 | 0.215 | 0.013 | -0.008 | -0.040 | 0.043 | 0.051 | 0.021 | 0.206 | 0.698 |
| 19 | Kazkommertsbank | 2011 | 0.166 | 0.123 | 0.111 | 0.187 | 5.342 | 0.123 | 0.717 | 0.004 | 0.000 | 0.000 | 0.055 | 0.066 | 0.038 | 0.350 | 0.675 |
| 20 | Nurbank | 2011 | 0.188 | 0.164 | 0.200 | 0.226 | 4.420 | 0.304 | 1.241 | 0.011 | -0.370 | -1.965 | -0.326 | 0.033 | 0.009 | -0.081 | 0.797 |
| 21 | Qazaq Banki | 2011 | 0.400 | 0.395 | 0.475 | 0.668 | 1.498 | 0.009 | 0.012 | 0.035 | 0.005 | 0.013 | 0.050 | 0.096 | 0.054 | -0.389 | 2.185 |
| 22 | Shinhan Bank of Kazakhstan | 2011 | 0.933 | 0.930 | 1.405 | 13.831 | .072 | 0.000 | 0.000 | 0.033 | 0.002 | 0.003 | 0.021 | 0.053 | 0.035 | 0.270 | 4.671 |
| 23 | Temirbank* | 2011 | 0.150 | 0.081 | 0.090 | 0.163 | 6.121 | 0.470 | 3.461 | 0.015 | 0.390 | 20.601 | 0.457 | 0.022 | -0.016 | 0.401 | 3.732 |
| 24 | TPBK | 2011 | 0.338 | 0.313 | 1.833 | 0.510 | 1.960 | 0.000 | 0.000 | 0.003 | 0.025 | 0.073 | 0.031 | 0.018 | 0.010 | 0.288 | 1.410 |
| 25 | Tsesnabank | 2011 | 0.116 | 0.101 | 0.107 | 0.129 | 7.749 | 0.033 | 0.186 | 0.010 | 0.003 | 0.023 | 0.094 | 0.042 | 0.049 | -1.258 | 0.701 |
| 26 | Zaman-Bank | 2011 | 0.799 | 0.733 | 0.656 | 3.152 | .317 | 0.035 | 0.036 | 0.017 | 0.014 | 0.017 | 0.031 | 0.110 | 0.024 | 0.049 | 1.725 |
| 27 | SB Alpha-Bank | 2011 | 0.108 | 0.084 | 0.127 | 0.121 | 8.268 | 0.080 | 0.246 | 0.013 | 0.018 | 0.163 | 0.047 | 0.036 | 0.027 | -0.095 | 1.053 |
| 28 | SB Bank of China in Kazakhstan | 2011 | 0.206 | 0.180 | 0.761 | 0.260 | 3.846 | 0.000 | 0.000 | 0.003 | 0.024 | 0.118 | 0.031 | 0.008 | 0.008 | 0.034 | 1.133 |
| 29 | SB Home Credit and Finance Bank | 2011 | 0.430 | 0.214 | 0.216 | 0.666 | 1.502 | 0.051 | 0.090 | 0.034 | 0.129 | 0.299 | 0.170 | 0.524 | 0.436 | 0.000 | 1.494 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 30 | SB HSBC Bank Kazakhstan | 2011 | 0.057 | 0.075 | 0.354 | 0.061 | 16.468 | 0.049 | 0.311 | 0.013 | 0.008 | 0.138 | 0.016 | 0.044 | 0.039 | 0.066 | 0.870 |
| 31 | SB KZI Bank | 2011 | 0.556 | 0.520 | 0.913 | 1.256 | 0.796 | 0.237 | 0.147 | 0.018 | 0.009 | 0.017 | 0.016 | 0.061 | 0.004 | 0.375 | 1.451 |
| 32 | SB NB of Pakistan in Kazakhstan | 2011 | 0.808 | 0.787 | 0.856 | 4.192 | 0.239 | 0.003 | 0.003 | 0.027 | 0.018 | 0.022 | 0.031 | 0.112 | -0.015 | 0.091 | 2.167 |
| 33 | SB PNB – Kazakhstan | 2011 | 0.829 | 0.785 | 0.966 | 4.861 | 0.206 | 0.012 | 0.005 | 0.008 | 0.005 | 0.006 | -0.003 | 0.020 | -0.049 | 0.747 | 1.777 |
| 34 | SB RBS (Kazakhstan) | 2011 | 0.160 | 0.157 | 0.537 | 0.190 | 5.259 | 0.001 | 0.001 | 0.007 | -0.007 | -0.045 | -0.004 | 0.018 | 0.017 | -0.022 | 0.974 |
| 35 | SB Sberbank | 2011 | 0.143 | 0.129 | 0.155 | 0.166 | 6.010 | 0.050 | 0.219 | 0.013 | 0.009 | 0.064 | 0.061 | 0.053 | 0.051 | -0.078 | 0.661 |
| 36 | SB Taib Kazakh Bank | 2011 | 0.832 | 0.543 | 1.138 | 1.996 | 0.501 | 0.063 | 0.012 | 0.012 | 0.002 | 0.002 | 0.019 | 0.021 | 0.007 | 0.073 | 5.266 |
| 37 | SB VTB Bank (Kazakhstan) | 2011 | 0.384 | 0.384 | 0.549 | 0.624 | 1.602 | 0.000 | 0.000 | 0.032 | -0.027 | -0.071 | 0.125 | 0.057 | 0.048 | 1.329 | 4.260 |
| 38 | Credit Altyn Bank | 2011 | 0.873 | 0.873 | 1.348 | 6.887 | 0.145 | 0.000 | 0.000 | 0.450 | -0.013 | -0.014 | 0.060 | 0.027 | 0.027 | 0.798 | 7.360 |
| | | | | | | | | | | | | | | | | | |
| 2 | Alliance Bank* | 2010 | -0.841 | -0.841 | -0.451 | -0.458 | -2.184 | 0.708 | -0.798 | 0.043 | -1.133 | 1.353 | -1.062 | 0.006 | 0.004 | 0.122 | 1.390 |
| 3 | AsiaCredit Bank | 2010 | 0.536 | 0.450 | 0.752 | 1.155 | 0.866 | 0.045 | 0.032 | 0.060 | 0.023 | 0.043 | 0.032 | 0.098 | 0.086 | -0.130 | 1.842 |
| 4 | ATF Bank | 2010 | 0.142 | 0.102 | 0.151 | 0.156 | 6.400 | 0.096 | 0.530 | 0.017 | 0.001 | 0.015 | 0.055 | 0.043 | 0.032 | -0.405 | 1.985 |
| 5 | Bank Astana-Finance | 2010 | 0.429 | 0.433 | 0.439 | 0.753 | 1.329 | 0.016 | 0.028 | 0.028 | -0.039 | -0.091 | 0.015 | 0.074 | 0.045 | -0.613 | 0.994 |
| 6 | Bank Centercredit | 2010 | 0.134 | 0.088 | 0.129 | 0.145 | 6.906 | 0.042 | 0.181 | 0.015 | 0.001 | 0.017 | 0.071 | 0.059 | 0.047 | -0.626 | 1.953 |
| 7 | Bank Kassa Nova | 2010 | 0.999 | 0.999 | 0.958 | 2557.7 | 0.000 | 0.000 | 0.000 | 0.014 | -0.012 | -0.012 | -0.003 | 0.000 | 0.000 | 0.026 | 0.000 |
| 8 | Bank Positive Kazakhstan | 2010 | 0.415 | 0.350 | 0.640 | 0.638 | 1.567 | 0.325 | 0.273 | 0.019 | -0.101 | -0.289 | -0.091 | 0.076 | 0.066 | 0.071 | 1.581 |
| 9 | Bank RBK | 2010 | 0.851 | 0.722 | 0.785 | 5.469 | 0.183 | 0.002 | 0.002 | 0.004 | 0.009 | 0.010 | 0.001 | 0.160 | 0.155 | 1.158 | 1.358 |
| 10 | BTA Bank* | 2010 | -0.881 | -0.966 | -0.673 | -0.504 | -1.983 | 0.759 | -1.103 | 0.015 | -1.067 | 1.427 | -0.887 | -0.019 | -0.018 | -0.548 | 0.535 |
| 11 | Citibank of Kazakhstan | 2010 | 0.102 | 0.066 | 0.214 | 0.114 | 8.783 | 0.008 | 0.016 | 0.017 | 0.037 | 0.361 | 0.039 | 0.017 | 0.016 | -0.719 | 1.021 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 12 | Delta Bank | 2010 | 0.278 | 0.236 | 0.203 | 0.365 | 2.738 | 0.021 | 0.052 | 0.006 | 0.002 | 0.009 | 0.048 | 0.088 | 0.069 | 0.320 | 0.450 |
| 13 | Eurasian Bank | 2010 | 0.113 | 0.079 | 0.118 | 0.122 | 8.175 | 0.082 | 0.419 | 0.015 | -0.038 | -0.511 | 0.027 | 0.023 | 0.020 | -0.107 | 2.243 |
| 14 | Eximbank Kazakhstan | 2010 | 0.193 | 0.180 | 0.218 | 0.240 | 4.163 | 0.026 | 0.110 | 0.009 | 0.005 | 0.028 | 0.065 | 0.069 | 0.046 | -0.607 | 0.455 |
| 15 | ForteBank | 2010 | 0.216 | 0.216 | 0.214 | 0.275 | 3.631 | 0.184 | 0.633 | 0.015 | -0.187 | -0.866 | -0.081 | 0.217 | 0.164 | -0.110 | 1.353 |
| 16 | Halyk Bank of Kazakhstan | 2010 | 0.139 | 0.111 | 0.143 | 0.158 | 6.340 | 0.082 | 0.367 | 0.010 | 0.001 | 0.011 | 0.041 | 0.049 | 0.039 | -0.037 | 0.842 |
| 17 | Kaspi Bank | 2010 | 0.122 | 0.099 | 0.105 | 0.137 | 7.326 | 0.061 | 0.414 | 0.006 | 0.001 | 0.011 | 0.091 | 0.066 | 0.054 | -0.747 | 1.336 |
| 18 | Kazinvestbank | 2010 | 0.162 | 0.136 | 0.165 | 0.191 | 5.241 | 0.005 | 0.022 | 0.029 | 0.002 | 0.013 | 0.077 | 0.057 | 0.040 | 0.180 | 0.697 |
| 19 | Kazkommertsbank | 2010 | 0.173 | 0.128 | 0.110 | 0.195 | 5.124 | 0.120 | 0.685 | 0.005 | 0.000 | 0.000 | 0.057 | 0.095 | 0.062 | 0.390 | 0.588 |
| 20 | Nurbank | 2010 | 0.176 | 0.147 | 0.144 | 0.207 | 4.823 | 0.019 | 0.085 | 0.009 | 0.003 | 0.017 | 0.067 | 0.044 | 0.031 | 0.035 | 0.567 |
| 21 | Qazaq Banki | 2010 | 0.727 | 0.691 | 0.751 | 2.670 | 0.375 | 0.024 | 0.023 | 0.020 | 0.037 | 0.051 | 0.060 | 0.137 | 0.105 | -0.775 | 1.916 |
| 22 | Shinhan Bank of Kazakhstan | 2010 | 0.956 | 0.946 | 1.293 | 21.835 | 0.046 | 0.000 | 0.000 | 0.015 | 0.010 | 0.011 | 0.015 | 0.064 | 0.064 | 0.469 | 5.217 |
| 23 | Temirbank* | 2010 | -0.468 | -0.469 | -0.304 | -0.319 | -3.131 | 0.473 | -10.479 | 0.013 | -0.743 | 10.595 | -0.213 | -0.006 | -0.022 | 0.476 | 0.983 |
| 24 | TPBK | 2010 | 0.307 | 0.291 | 1.379 | 0.443 | 2.257 | 0.000 | 0.000 | 0.003 | 0.016 | 0.054 | 0.015 | 0.031 | 0.030 | 0.051 | 1.869 |
| 25 | Tsesnabank | 2010 | 0.123 | 0.092 | 0.094 | 0.137 | 7.313 | 0.033 | 0.198 | 0.008 | 0.010 | 0.096 | 0.090 | 0.062 | 0.053 | -0.811 | 0.732 |
| 26 | Zaman-Bank | 2010 | 0.782 | 0.772 | 0.385 | 3.587 | 0.279 | 0.007 | 0.008 | 0.012 | 0.010 | 0.012 | -0.001 | 0.105 | 0.099 | 0.103 | 1.980 |
| 27 | SB Alpha-Bank | 2010 | 0.161 | 0.146 | 0.244 | 0.191 | 5.224 | 0.164 | 0.345 | 0.004 | 0.004 | 0.027 | 0.032 | 0.041 | 0.026 | -0.376 | 1.505 |
| 28 | SB Bank of China in Kazakhstan | 2010 | 0.159 | 0.134 | 10.536 | 0.189 | 5.282 | 0.000 | 0.000 | 0.003 | 0.025 | 0.156 | 0.021 | 0.011 | 0.011 | 0.029 | 1.082 |
| 29 | SB Home Credit and Finance Bank | 2010 | 0.461 | 0.301 | 0.431 | 0.691 | 1.448 | 0.214 | 0.337 | 0.027 | 0.021 | 0.064 | 0.051 | 0.459 | 0.285 | 0.040 | 1.707 |
| 30 | SB HSBC Bank Kazakhstan | 2010 | 0.053 | 0.071 | 0.219 | 0.057 | 17.696 | 0.037 | 0.302 | 0.008 | -0.001 | -0.014 | 0.002 | 0.028 | 0.027 | -0.486 | 0.692 |
| 31 | SB KZI Bank | 2010 | 0.506 | 0.481 | 0.826 | 1.026 | 0.975 | 0.158 | 0.121 | 0.031 | 0.000 | 0.001 | -0.005 | 0.070 | 0.060 | 0.248 | 1.583 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 32 | SB NB of Pakistan in Kazakhstan | 2010 | 0.425 | 0.412 | 0.504 | 0.733 | 1.365 | 0.006 | 0.006 | 0.023 | 0.008 | 0.018 | 0.005 | 0.088 | 0.085 | -0.143 | 0.841 |
| 33 | SB PNB – Kazakhstan | 2010 | 0.559 | 0.531 | 0.428 | 1.269 | 0.788 | 0.257 | 0.252 | 0.046 | 0.018 | 0.032 | 0.070 | 0.170 | 0.082 | 0.947 | 0.717 |
| 34 | SB RBS (Kazakhstan) | 2010 | 0.118 | 0.114 | 0.495 | 0.134 | 7.485 | 0.066 | 0.102 | 0.017 | 0.002 | 0.020 | 0.010 | 0.026 | 0.022 | -5.220 | 1.032 |
| 35 | SB Sberbank | 2010 | 0.173 | 0.155 | 0.248 | 0.207 | 4.830 | 0.060 | 0.151 | 0.015 | 0.010 | 0.062 | 0.048 | 0.057 | 0.044 | -0.077 | 1.713 |
| 36 | SB Taib Kazakh Bank | 2010 | 0.522 | 0.323 | 0.480 | 0.808 | 1.238 | 0.058 | 0.026 | 0.020 | -0.023 | -0.065 | -0.002 | 0.060 | 0.043 | 0.312 | 6.922 |
| 37 | SB VTB Bank (Kazakhstan) | 2010 | 0.509 | 0.509 | 1.878 | 1.035 | 0.966 | 0.000 | 0.000 | 0.028 | -0.014 | -0.028 | -0.065 | 0.035 | 0.034 | 0.972 | 1.945 |
| 39 | Maserbank | 2010 | 0.777 | 0.746 | 0.811 | 3.475 | 0.288 | 0.201 | 0.188 | 0.098 | -0.082 | -0.106 | -0.081 | 0.169 | 0.149 | 0.719 | 6.862 |
| | | | | | | | | | | | | | | | | | |
| 2 | Alliance Bank* | 2009 | 0.185 | 0.166 | 0.193 | 0.219 | 4.572 | 0.033 | 0.120 | 0.009 | 0.001 | 0.010 | 0.084 | 0.042 | 0.038 | 0.098 | 1.577 |
| 3 | AsiaCredit Bank | 2009 | 0.632 | 0.480 | 0.782 | 1.719 | 0.582 | 0.002 | 0.002 | 0.047 | 0.040 | 0.063 | 0.051 | 0.060 | 0.056 | 0.345 | 2.002 |
| 4 | ATF Bank | 2009 | 0.128 | 0.090 | 0.129 | 0.139 | 7.196 | 0.054 | 0.341 | 0.007 | -0.028 | -0.373 | 0.041 | 0.023 | 0.022 | -0.376 | 0.358 |
| 5 | Bank Astana-Finance | 2009 | 0.292 | 0.292 | 0.309 | 0.413 | 2.423 | 0.000 | 0.000 | 0.011 | -0.012 | -0.040 | 0.099 | 0.011 | 0.008 | -0.814 | 0.223 |
| 6 | Bank Centercredit | 2009 | 0.154 | 0.103 | 0.186 | 0.171 | 5.863 | 0.024 | 0.108 | 0.010 | 0.006 | 0.066 | 0.091 | 0.026 | 0.025 | -0.651 | 0.295 |
| 8 | Bank Positive Kazakhstan | 2009 | 0.351 | 0.349 | 0.374 | 0.542 | 1.846 | 0.023 | 0.037 | 0.066 | 0.002 | 0.007 | 0.001 | 0.049 | 0.047 | 0.031 | 1.068 |
| 9 | Bank RBK | 2009 | 0.903 | 0.744 | 0.911 | 9.354 | 0.107 | 0.000 | 0.000 | 0.082 | 0.011 | 0.012 | 0.014 | 0.088 | 0.087 | 0.879 | 6.096 |
| 10 | BTA Bank* | 2009 | 0.186 | 0.139 | 0.132 | 0.217 | 4.615 | 0.042 | 0.180 | 0.005 | 0.004 | 0.030 | 0.014 | 0.031 | 0.028 | -0.574 | 0.119 |
| 11 | Citibank of Kazakhstan | 2009 | 0.125 | 0.095 | 0.229 | 0.143 | 7.015 | 0.138 | 0.337 | 0.007 | 0.032 | 0.254 | 0.062 | 0.019 | 0.018 | -0.358 | 0.696 |
| 12 | Delta Bank | 2009 | 0.347 | 0.226 | 0.301 | 0.451 | 2.216 | 0.014 | 0.032 | 0.029 | 0.008 | 0.033 | 0.060 | 0.046 | 0.040 | 0.141 | 1.168 |
| 13 | Eurasian Bank | 2009 | 0.138 | 0.089 | 0.170 | 0.152 | 6.561 | 0.011 | 0.039 | 0.011 | 0.006 | 0.063 | 0.126 | 0.020 | 0.019 | 0.138 | 1.782 |
| 14 | Eximbank Kazakhstan | 2009 | 0.240 | 0.224 | 0.270 | 0.316 | 3.161 | 0.017 | 0.054 | 0.010 | 0.007 | 0.030 | 0.084 | 0.036 | 0.027 | -0.572 | 0.238 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 15 | ForteBank | 2009 | 0.292 | 0.292 | 0.228 | 0.413 | 2.421 | 0.104 | 0.296 | 0.045 | -0.013 | -0.043 | 0.036 | 0.134 | 0.122 | 0.162 | 1.230 |
| 16 | Halyk Bank of Kazakhstan | 2009 | 0.128 | 0.086 | 0.123 | 0.143 | 7.017 | 0.043 | 0.256 | 0.009 | 0.006 | 0.058 | 0.072 | 0.029 | 0.028 | 0.068 | 1.274 |
| 17 | Kaspi Bank | 2009 | 0.152 | 0.113 | 0.141 | 0.173 | 5.781 | 0.046 | 0.226 | 0.018 | 0.005 | 0.042 | 0.097 | 0.055 | 0.052 | -0.807 | 0.130 |
| 18 | Kazinvestbank | 2009 | 0.172 | 0.154 | 0.185 | 0.204 | 4.892 | 0.000 | 0.000 | 0.016 | 0.003 | 0.021 | 0.087 | 0.028 | 0.023 | -0.309 | 0.473 |
| 19 | Kazkommertsbank | 2009 | 0.153 | 0.110 | 0.133 | 0.167 | 6.003 | 0.059 | 0.356 | 0.004 | 0.000 | 0.005 | 0.076 | 0.045 | 0.042 | 0.425 | 1.653 |
| 20 | Nurbank | 2009 | 0.169 | 0.147 | 0.155 | 0.199 | 5.023 | 0.031 | 0.152 | 0.011 | 0.004 | 0.024 | 0.074 | 0.024 | 0.018 | -0.173 | 0.306 |
| 21 | Qazaq Banki | 2009 | 0.749 | 0.734 | 0.735 | 2.982 | .335 | 0.010 | 0.012 | 0.034 | 0.015 | 0.020 | 0.034 | 0.062 | 0.044 | -0.030 | 0.898 |
| 22 | Shinhan Bank of Kazakhstan | 2009 | 0.991 | 0.991 | 0.966 | 108.888 | .009 | 0.000 | 0.000 | 0.011 | -0.024 | -0.025 | -0.024 | 0.026 | 0.026 | 0.737 | 17.791 |
| 23 | Temirbank* | 2009 | 0.185 | 0.182 | 0.149 | 0.226 | 4.425 | 0.042 | 0.202 | 0.013 | -0.006 | -0.033 | 0.336 | 0.024 | 0.016 | 0.342 | 1.815 |
| 24 | TPBK | 2009 | 0.401 | 0.349 | 20.092 | 0.669 | 1.494 | 0.000 | 0.000 | 0.013 | 0.051 | 0.128 | 0.058 | 0.023 | 0.023 | 20.022 | 11.109 |
| 25 | Tsesnabank | 2009 | 0.139 | 0.100 | 0.129 | 0.157 | 6.387 | 0.041 | 0.194 | 0.023 | -0.043 | -0.378 | 0.042 | 0.024 | 0.022 | -0.580 | 0.393 |
| 26 | Zaman-Bank | 2009 | 0.928 | 0.908 | 0.690 | 12.971 | 0.077 | 0.016 | 0.017 | 0.029 | 0.020 | 0.022 | 0.057 | 0.065 | 0.065 | 0.152 | 1.714 |
| 27 | SB Alpha-Bank | 2009 | 0.260 | 0.196 | 0.377 | 0.351 | 2.846 | 0.014 | 0.032 | 0.026 | 0.052 | 0.201 | 0.104 | 0.043 | 0.039 | -0.072 | 0.937 |
| 28 | SB Bank of China in Kazakhstan | 2009 | 0.116 | 0.097 | 0.861 | 0.131 | 7.638 | 0.000 | 0.000 | 0.004 | 0.019 | 0.163 | 0.037 | 0.015 | 0.014 | 0.046 | 1.030 |
| 29 | SB Home Credit and Finance Bank | 2009 | 0.314 | 0.314 | 0.252 | 0.459 | 2.180 | 0.012 | 0.032 | 0.024 | -0.003 | -0.010 | 0.054 | 0.060 | 0.056 | 0.016 | 29.006 |
| 30 | SB HSBC Bank Kazakhstan | 2009 | 0.100 | 0.087 | 0.144 | 0.111 | 9.002 | 0.000 | 0.001 | 0.010 | 0.013 | 0.129 | 0.045 | 0.013 | 0.011 | 0.075 | 1.046 |
| 31 | SB KZI Bank | 2009 | 0.462 | 0.410 | 0.388 | 0.861 | 1.161 | 0.077 | 0.120 | 0.039 | 0.008 | 0.017 | 0.010 | 0.056 | 0.055 | -0.252 | 0.700 |
| 32 | SB NB of Pakistan in Kazakhstan | 2009 | 0.544 | 0.528 | 0.581 | 1.175 | 0.851 | 0.000 | 0.000 | 0.026 | 0.009 | 0.016 | 0.014 | 0.046 | 0.045 | 0.652 | 4.481 |
| 33 | SB PNB – Kazakhstan | 2009 | 0.533 | 0.525 | 0.412 | 1.140 | 0.878 | 0.251 | 0.334 | 0.076 | -0.218 | -0.409 | -0.184 | 0.081 | 0.073 | -0.186 | 0.287 |
| 34 | SB RBS (Kazakhstan) | 2009 | 0.120 | 0.106 | 0.325 | 0.136 | 7.358 | 0.004 | 0.013 | 0.016 | 0.013 | 0.106 | 0.037 | 0.017 | 0.015 | -0.125 | 0.864 |
| 35 | SB Sberbank | 2009 | 0.378 | 0.327 | 0.410 | 0.582 | 1.717 | 0.045 | 0.094 | 0.021 | 0.024 | 0.068 | 0.089 | 0.048 | 0.038 | 0.173 | 1.108 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 36 | SB Taib Kazakh Bank | 2009 | 0.794 | 0.770 | 0.970 | 3.873 | 0.258 | 0.000 | 0.000 | 0.039 | 0.020 | 0.025 | 0.041 | 0.036 | 0.026 | 0.502 | 1.989 |
| 39 | Maserbank | 2009 | 0.761 | 0.723 | 0.879 | 3.187 | 0.314 | 0.000 | 0.000 | 0.051 | 0.039 | 0.051 | 0.026 | 0.086 | 0.081 | 0.729 | 3.996 |
| 40 | Express Bank | 2009 | 0.876 | 0.876 | 0.601 | 7.036 | 0.142 | 0.000 | 0.000 | 0.040 | -0.104 | -0.119 | 0.050 | 0.067 | 0.041 | 0.050 | 0.000 |
| | | | | | | | | | | | | | | | | | |
| 2 | Alliance Bank* | 2008 | 0.156 | 0.113 | 0.143 | 0.180 | 5.557 | 0.014 | 0.063 | 0.008 | 0.031 | 0.200 | 0.078 | 0.048 | 0.045 | 0.051 | 3.009 |
| 3 | AsiaCredit Bank | 2008 | 0.614 | 0.392 | 0.801 | 1.593 | 0.628 | 0.013 | 0.011 | 0.034 | 0.053 | 0.087 | 0.077 | 0.057 | 0.052 | 0.260 | 0.717 |
| 4 | ATF Bank | 2008 | 0.131 | 0.085 | 0.142 | 0.142 | 7.033 | 0.010 | 0.061 | 0.006 | 0.006 | 0.047 | 0.047 | 0.020 | 0.018 | -0.360 | 1.594 |
| 6 | Bank Centercredit | 2008 | 0.122 | 0.073 | 0.128 | 0.133 | 7.529 | 0.010 | 0.059 | 0.008 | 0.016 | 0.128 | 0.058 | 0.026 | 0.024 | -0.644 | 1.297 |
| 8 | Bank Positive Kazakhstan | 2008 | 0.329 | 0.306 | 0.379 | 0.491 | 2.035 | 0.009 | 0.015 | 0.039 | 0.023 | 0.070 | 0.031 | 0.032 | 0.031 | -0.168 | 0.744 |
| 9 | Bank RBK | 2008 | 0.830 | 0.689 | 0.868 | 4.895 | 0.204 | 0.000 | 0.000 | 0.044 | 0.013 | 0.015 | 0.007 | 0.088 | 0.088 | 0.566 | 0.957 |
| 10 | BTA Bank* | 2008 | 0.179 | 0.136 | 0.138 | 0.211 | 4.732 | 0.006 | 0.025 | 0.006 | 0.018 | 0.103 | 0.054 | 0.023 | 0.020 | -0.525 | 1.485 |
| 11 | Citibank of Kazakhstan | 2008 | 0.144 | 0.084 | 0.240 | 0.163 | 6.141 | 0.020 | 0.056 | 0.008 | 0.031 | 0.217 | 0.052 | 0.018 | 0.017 | -0.487 | 1.155 |
| 12 | Delta Bank | 2008 | 0.430 | 0.275 | 0.297 | 0.606 | 1.651 | 0.013 | 0.025 | 0.031 | 0.015 | 0.035 | 0.052 | 0.033 | 0.027 | 0.351 | 0.389 |
| 13 | Eurasian Bank | 2008 | 0.156 | 0.095 | 0.164 | 0.175 | 5.719 | 0.016 | 0.068 | 0.016 | 0.014 | 0.088 | 0.050 | 0.026 | 0.024 | -0.165 | 1.289 |
| 14 | Eximbank Kazakhstan | 2008 | 0.303 | 0.278 | 0.293 | 0.436 | 2.293 | 0.005 | 0.013 | 0.011 | 0.014 | 0.047 | 0.055 | 0.036 | 0.028 | -0.370 | 0.595 |
| 15 | ForteBank | 2008 | 0.634 | 0.617 | 0.634 | 1.732 | 0.577 | 0.000 | 0.000 | 0.003 | 0.017 | 0.026 | 0.015 | 0.074 | 0.000 | 0.485 | 1.168 |
| 16 | Halyk Bank of Kazakhstan | 2008 | 0.112 | 0.070 | 0.120 | 0.123 | 8.151 | 0.019 | 0.117 | 0.010 | 0.021 | 0.187 | 0.057 | 0.031 | 0.028 | -0.127 | 1.192 |
| 17 | Kaspi Bank | 2008 | 0.142 | 0.089 | 0.128 | 0.161 | 6.222 | 0.034 | 0.178 | 0.019 | 0.023 | 0.159 | 0.060 | 0.068 | 0.063 | -0.577 | 1.380 |
| 18 | Kazinvestbank | 2008 | 0.205 | 0.149 | 0.256 | 0.245 | 4.079 | 0.002 | 0.005 | 0.012 | 0.016 | 0.079 | 0.059 | 0.025 | 0.020 | -0.369 | 1.108 |
| 19 | Kazkommertsbank | 2008 | 0.132 | 0.083 | 0.123 | 0.146 | 6.827 | 0.022 | 0.137 | 0.004 | 0.017 | 0.129 | 0.053 | 0.028 | 0.025 | 0.444 | 1.350 |
| 20 | Nurbank | 2008 | 0.223 | 0.173 | 0.209 | 0.275 | 3.636 | 0.023 | 0.075 | 0.000 | 0.015 | 0.067 | 0.049 | 0.016 | 0.011 | -0.164 | 1.610 |
| 21 | Qazaq Banki | 2008 | 0.695 | 0.654 | 0.722 | 2.282 | 0.438 | 0.000 | 0.000 | 0.033 | 0.042 | 0.060 | 0.059 | 0.057 | 0.046 | -0.230 | 1.660 |
| 23 | Temirbank* | 2008 | 0.166 | 0.141 | 0.141 | 0.199 | 5.024 | 0.026 | 0.131 | 0.013 | 0.025 | 0.149 | 0.079 | 0.039 | 0.034 | 0.237 | 1.558 |
| 24 | TPBK | 2008 | 0.371 | 0.325 | 3.872 | 0.591 | | 0.000 | 0.000 | 0.012 | 0.046 | 0.123 | | 0.024 | 0.023 | | 0.938 |

**Source:** Author

Continuation of Appendix 3A

| Bank's codes | Bank's Names | Year | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 25 | Tsesnabank | 2008 | 0.155 | 0.112 | 0.140 | 0.178 | 5.626 | 0.015 | 0.074 | 0.021 | 0.007 | 0.045 | 0.053 | 0.025 | 0.022 | -0.390 | 1.156 |
| 26 | Zaman-Bank | 2008 | 0.972 | 0.938 | 0.810 | 34.943 | 0.029 | 0.064 | 0.068 | 0.035 | 0.034 | 0.035 | .050 | .061 | .054 | .103 | 1.398 |
| 27 | SB Alpha-Bank | 2008 | 0.268 | 0.189 | 0.294 | 0.366 | 2.734 | 0.013 | 0.034 | 0.021 | 0.041 | 0.155 | 0.078 | 0.036 | 0.033 | 0.219 | 0.504 |
| 28 | SB Bank of China in Kazakhstan | 2008 | 0.469 | 0.416 | 10.467 | 0.883 | 1.133 | 0.000 | 0.000 | 0.029 | 0.051 | 0.109 | 0.093 | 0.019 | 0.018 | 0.109 | 1.381 |
| 29 | SB Home Credit and Finance Bank | 2008 | 0.363 | 0.313 | 0.464 | 0.569 | 1.756 | 0.195 | 0.168 | 0.034 | 0.049 | 0.136 | 0.200 | 0.010 | 0.009 | 0.100 | 1.549 |
| 30 | SB HSBC Bank Kazakhstan | 2008 | 0.109 | 0.090 | 0.308 | 0.123 | 8.137 | 0.000 | 0.000 | 0.021 | 0.021 | 0.190 | 0.042 | 0.014 | 0.012 | -0.622 | 1.766 |
| 31 | SB KZI Bank | 2008 | 0.315 | 0.255 | 0.419 | 0.461 | 2.169 | 0.003 | 0.004 | 0.022 | 0.030 | 0.094 | 0.032 | 0.042 | 0.042 | -0.237 | 0.938 |
| 32 | SB NB of Pakistan in Kazakhstan | 2008 | 0.764 | 0.734 | 0.841 | 3.031 | 0.330 | 0.000 | 0.000 | 0.010 | 0.013 | 0.017 | 0.018 | 0.035 | 0.032 | 0.493 | 1.120 |
| 33 | SB PNB – Kazakhstan | 2008 | 0.376 | 0.350 | 0.330 | 0.602 | 1.661 | 0.029 | 0.061 | 0.048 | 0.020 | 0.054 | 0.035 | 0.046 | 0.035 | -0.046 | 0.877 |
| 34 | SB RBS (Kazakhstan) | 2008 | 0.154 | 0.133 | 0.332 | 0.179 | 5.574 | 0.000 | 0.000 | 0.017 | 0.011 | 0.072 | 0.043 | 0.021 | 0.020 | -0.363 | 1.302 |
| 35 | SB Sberbank | 2008 | 0.636 | 0.496 | 0.482 | 1.500 | 0.667 | 0.039 | 0.036 | 0.021 | 0.021 | 0.034 | 0.046 | 0.046 | 0.038 | 0.451 | 1.736 |
| 36 | SB Taib Kazakh Bank | 2008 | 0.637 | 0.609 | 0.965 | 1.764 | 0.567 | 0.000 | 0.000 | 0.016 | 0.022 | 0.035 | 0.026 | 0.026 | 0.018 | -0.188 | 1.380 |
| 39 | Maserbank | 2008 | 0.998 | 0.989 | 1.058 | 548.843 | | 0.000 | 0.000 | 0.000 | 0.008 | 0.008 | 0.000 | 0.036 | 0.000 | 0.000 | 986.375 |
| 40 | Express Bank | 2008 | 0.855 | 0.854 | 0.745 | 6.014 | 0.166 | 0.008 | 0.009 | 0.040 | -0.162 | -0.189 | 0.050 | 0.030 | -0.013 | 0.050 | 1.762 |

**Source:** Author

## Appendix 3B: Descriptive statistics

| | | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| N | Valid | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 | 256 |
| | Missing | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Mean | | 0.327 | 0.289 | 0.462 | 13.879 | 3.944 | 0.088 | 0.482 | 0.020 | -0.002 | 0.087 | 0.041 | 0.056 | 0.041 | -0.075 | 5.765 |
| Median | | 0.188 | 0.166 | 0.232 | 0.228 | 4.234 | 0.033 | 0.080 | 0.015 | 0.009 | 0.030 | 0.046 | 0.048 | 0.034 | 0.015 | 1.151 |
| Mode | | 0.123 | 0.070[a] | 0.094 | 0.140[a] | -3,131[a] | 0.000 | 0.000 | 0.013 | 0.018 | 0.075 | 0.032[a] | -,044[a] | 0.000 | 0.050[a] | 0.000[a] |
| Std. Deviation | | 0.289 | 0.286 | 0.572 | 163.403 | 3.195 | 0.143 | 2.052 | 0.031 | 0.132 | 0.520 | 0.125 | 0.058 | 0.049 | 0.591 | 61.632 |
| Skewness | | 0.280 | 0.330 | 3.374 | 15.051 | 0.630 | 2.824 | 11.171 | 11.117 | -4.528 | 6.238 | -3.082 | 4.607 | 4.107 | -2.854 | 15.920 |
| Std. Error of Skewness | | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 | 0.152 |
| Kurtosis | | 1.566 | 1.928 | 17.41 | 233.24 | 0.961 | 9.229 | 148.76 | 153.77 | 44.806 | 63.088 | 41.34 | 29.32 | 25.944 | 23.251 | 254.26 |
| Std. Error of Kurtosis | | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 | 0.303 |
| Minimum | | -0.881 | -0.966 | -0.673 | -0.504 | -3.131 | 0.000 | -1.479 | 0.000 | -1.133 | -1.965 | -1.062 | -0.044 | -0.049 | -5.220 | 0.000 |
| Maximum | | 0.999 | 0.999 | 4.528 | 2557.67 | 17.7 | 0.850 | 29.001 | 0.450 | 0.651 | 5.730 | 0.733 | 0.524 | 0.436 | 2.022 | 986.38 |

Multiple modes exist. The smallest value is shown[a]

## Appendix 3C: Tests of Normality

| | Kolmogorov-Smirnov[a] | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| R1 | 0.198 | 256 | 0.000 | 0.839 | 256 | 0.000 |
| R2 | 0.199 | 256 | 0.000 | 0.837 | 256 | 0.000 |
| R3 | 0.232 | 256 | 0.000 | 0.680 | 256 | 0.000 |
| R4 | 0.481 | 256 | 0.000 | 0.056 | 256 | 0.000 |
| R5 | 0.104 | 256 | 0.000 | 0.931 | 256 | 0.000 |
| R6 | 0.270 | 256 | 0.000 | 0.633 | 256 | 0.000 |
| R7 | 0.395 | 256 | 0.000 | 0.223 | 256 | 0.000 |
| R8 | 0.264 | 256 | 0.000 | 0.349 | 256 | 0.000 |
| R9 | 0.333 | 256 | 0.000 | 0.364 | 256 | 0.000 |
| R10 | 0.334 | 256 | 0.000 | 0.382 | 256 | 0.000 |
| R11 | 0.273 | 256 | 0.000 | 0.491 | 256 | 0.000 |
| R12 | 0.210 | 256 | 0.000 | 0.605 | 256 | 0.000 |
| R13 | 0.188 | 256 | 0.000 | 0.668 | 256 | 0.000 |
| R14 | 0.127 | 256 | 0.000 | 0.807 | 256 | 0.000 |
| R15 | 0.465 | 256 | 0.000 | 0.049 | 256 | 0.000 |

a. Lilliefors Significance Correction

**Appendix 3D: The Ranking Scores of the Capital Adequacy, 2008**

| Banks | R1 | Rank | R2 | Rank | R3 | Rank | R5 | Rank | Total |
|---|---|---|---|---|---|---|---|---|---|
| Masterbank | 0.998 | 10 | 0.989 | 10 | 1.058 | 3 | 0.002 | 10 | 33 |
| SB Bank of China in Kazakhstan | 0.469 | 5 | 0.416 | 4 | 1.467 | 4 | 1.133 | 9 | 22 |
| Senim-Bank | 0.695 | 7 | 0.654 | 7 | 0.722 | 2 | 0.438 | 10 | 26 |
| SB Lariba-Bank | 0.614 | 6 | 0.392 | 4 | 0.801 | 2 | 0.628 | 10 | 22 |
| Zaman-Bank | 0.972 | 10 | 0.938 | 10 | 0.81 | 2 | 0.029 | 10 | 32 |
| TPBK | 0.371 | 3 | 0.325 | 3 | 3.872 | 10 | 1.692 | 8 | 24 |
| Express Bank | 0.855 | 9 | 0.854 | 9 | 0.745 | 2 | 0.166 | 10 | 30 |
| SB NB of Pakistan in Kazakhstan | 0.764 | 8 | 0.734 | 8 | 0.841 | 2 | 0.33 | 10 | 28 |
| SB Alfa-Bank | 0.268 | 2 | 0.189 | 2 | 0.294 | 1 | 2.734 | 7 | 12 |
| SB Taib Kazakh Bank | 0.637 | 6 | 0.609 | 6 | 0.965 | 3 | 0.567 | 10 | 25 |
| Kazinkombank | 0.83 | 9 | 0.689 | 7 | 0.868 | 2 | 0.204 | 10 | 28 |
| SB Sberbank of Russia | 0.636 | 6 | 0.496 | 5 | 0.482 | 1 | 0.667 | 10 | 22 |
| Delta Bank | 0.43 | 4 | 0.275 | 3 | 0.297 | 1 | 1.651 | 8 | 16 |
| Eximbank Kazakhstan | 0.303 | 3 | 0.278 | 3 | 0.293 | 1 | 2.293 | 8 | 15 |
| Metrokombank | 0.634 | 6 | 0.617 | 6 | 0.634 | 2 | 0.577 | 10 | 24 |
| MB Alma-Ata | 0.363 | 3 | 0.313 | 3 | 0.464 | 1 | 1.756 | 8 | 15 |
| Alliance Bank | 0.156 | 1 | 0.113 | 1 | 0.143 | 1 | 5.557 | 4 | 7 |
| Kazinvestbank | 0.205 | 2 | 0.149 | 1 | 0.256 | 1 | 4.079 | 5 | 9 |
| SB KZI bank | 0.315 | 3 | 0.255 | 3 | 0.419 | 1 | 2.169 | 8 | 15 |
| Demir Kazakhstan Bank | 0.329 | 3 | 0.306 | 3 | 0.379 | 1 | 2.035 | 8 | 15 |
| Danabank | 0.376 | 4 | 0.35 | 4 | 0.33 | 1 | 1.661 | 8 | 17 |
| Bank Turanalem | 0.179 | 1 | 0.136 | 1 | 0.138 | 1 | 4.732 | 5 | 8 |
| Nurbank | 0.223 | 2 | 0.173 | 2 | 0.209 | 1 | 3.636 | 6 | 11 |
| DO Temirbank | 0.166 | 1 | 0.141 | 1 | 0.141 | 1 | 5.024 | 4 | 7 |
| SB ABN Amro Bank | 0.154 | 1 | 0.133 | 1 | 0.332 | 1 | 5.574 | 4 | 7 |
| Bank CenterCredit | 0.122 | 1 | 0.073 | 1 | 0.128 | 1 | 7.529 | 1 | 4 |
| Eurasian Bank | 0.156 | 1 | 0.095 | 1 | 0.164 | 1 | 5.719 | 3 | 6 |
| Citibank Kazakhstan | 0.144 | 1 | 0.084 | 1 | 0.24 | 1 | 6.141 | 3 | 6 |
| Tsesnabank | 0.155 | 1 | 0.112 | 1 | 0.14 | 1 | 5.626 | 4 | 7 |
| SB HSBC Bank of Kazakhstan | 0.109 | 1 | 0.09 | 1 | 0.308 | 1 | 8.137 | 1 | 4 |
| ATF Bank | 0.131 | 1 | 0.085 | 1 | 0.142 | 1 | 7.033 | 2 | 5 |
| Halyk Bank of Kazakhstan | 0.112 | 1 | 0.07 | 1 | 0.12 | 1 | 8.151 | 1 | 4 |
| Bank Caspian | 0.142 | 1 | 0.089 | 1 | 0.128 | 1 | 6.222 | 3 | 6 |
| Kazkommertsbank | 0.132 | 1 | 0.083 | 1 | 0.123 | 1 | 6.827 | 2 | 5 |

### Appendix 3E: The Ranking Scores of the Return on Assets, 2008

| Banks | R9 | Rank | R11 | Rank | Total |
|---|---|---|---|---|---|
| Masterbank | 0.008 | 8 | 0.026 | 1 | 9 |
| SB Bank of China in Kazakhstan | 0.051 | 10 | 0.093 | 5 | 15 |
| Senim-Bank | 0.042 | 10 | 0.059 | 3 | 13 |
| SB Lariba-Bank | 0.053 | 10 | 0.077 | 4 | 14 |
| Zaman-Bank | 0.034 | 10 | 0.05 | 3 | 13 |
| TPBK | 0.046 | 10 | 0.062 | 3 | 13 |
| Express Bank | -0.162 | 1 | 0.05 | 3 | 4 |
| SB NB of Pakistan in Kazakhstan | 0.013 | 9 | 0.018 | 1 | 10 |
| SB Alfa-Bank | 0.041 | 10 | 0.078 | 4 | 14 |
| SB Taib Kazakh Bank | 0.022 | 9 | 0.026 | 1 | 10 |
| Kazinkombank | 0.013 | 9 | 0.007 | 1 | 10 |
| SB Sberbank of Russia | 0.021 | 9 | 0.046 | 3 | 12 |
| Delta Bank | 0.015 | 9 | 0.052 | 3 | 12 |
| Eximbank Kazakhstan | 0.014 | 9 | 0.055 | 3 | 12 |
| Metrokombank | 0.017 | 9 | 0.015 | 1 | 10 |
| MB Alma-Ata | 0.049 | 10 | 0.2 | 10 | 20 |
| Alliance Bank | 0.031 | 9 | 0.078 | 4 | 13 |
| Kazinvestbank | 0.016 | 9 | 0.059 | 3 | 12 |
| SB KZI bank | 0.03 | 9 | 0.032 | 2 | 11 |
| Demir Kazakhstan Bank | 0.023 | 9 | 0.031 | 2 | 11 |
| Danabank | 0.02 | 9 | 0.035 | 2 | 11 |
| Bank Turanalem | 0.018 | 9 | 0.054 | 3 | 12 |
| Nurbank | 0.015 | 9 | 0.049 | 3 | 12 |
| DO Temirbank | 0.025 | 9 | 0.079 | 4 | 13 |
| SB ABN Amro Bank | 0.011 | 9 | 0.043 | 2 | 11 |
| Bank CenterCredit | 0.016 | 9 | 0.058 | 3 | 12 |
| Eurasian Bank | 0.014 | 9 | 0.05 | 3 | 12 |
| Citibank Kazakhstan | 0.031 | 9 | 0.052 | 3 | 12 |
| Tsesnabank | 0.007 | 8 | 0.053 | 3 | 11 |
| SB HSBC Bank of Kazakhstan | 0.021 | 9 | 0.042 | 2 | 11 |
| ATF Bank | 0.006 | 8 | 0.047 | 3 | 11 |
| Halyk Bank of Kazakhstan | 0.021 | 9 | 0.057 | 3 | 12 |
| Bank Caspian | 0.023 | 9 | 0.06 | 3 | 12 |
| Kazkommertsbank | 0.017 | 9 | 0.053 | 3 | 12 |

**Appendix 3F: The Ranking Scores of the Profitability, 2008**

| Banks | R12 | Rank | R13 | Rank | Total |
|---|---|---|---|---|---|
| Masterbank | 0.026 | 3 | 0.026 | 4 | 7 |
| SB Bank of China in Kazakhstan | 0.093 | 10 | 0.093 | 10 | 20 |
| Senim-Bank | 0.059 | 7 | 0.059 | 8 | 15 |
| SB Lariba-Bank | 0.077 | 9 | 0.077 | 9 | 18 |
| Zaman-Bank | 0.05 | 6 | 0.05 | 7 | 13 |
| TPBK | 0.062 | 7 | 0.062 | 8 | 15 |
| Express Bank | 0.05 | 6 | 0.05 | 7 | 13 |
| SB NB of Pakistan in Kazakhstan | 0.018 | 2 | 0.018 | 4 | 6 |
| SB Alfa-Bank | 0.078 | 9 | 0.078 | 10 | 19 |
| SB Taib Kazakh Bank | 0.026 | 3 | 0.026 | 4 | 7 |
| Kazinkombank | 0.007 | 1 | 0.007 | 2 | 3 |
| SB Sberbank of Russia | 0.046 | 5 | 0.046 | 6 | 11 |
| Delta Bank | 0.052 | 6 | 0.052 | 7 | 13 |
| Eximbank Kazakhstan | 0.055 | 6 | 0.055 | 7 | 13 |
| Metrokombank | 0.015 | 1 | 0.015 | 3 | 4 |
| MB Alma-Ata | 0.2 | 10 | 0.2 | 10 | 20 |
| Alliance Bank | 0.078 | 9 | 0.078 | 10 | 19 |
| Kazinvestbank | 0.059 | 7 | 0.059 | 8 | 15 |
| SB KZI bank | 0.032 | 3 | 0.032 | 5 | 8 |
| Demir Kazakhstan Bank | 0.031 | 3 | 0.031 | 5 | 8 |
| Danabank | 0.035 | 4 | 0.035 | 5 | 9 |
| Bank Turanalem | 0.054 | 6 | 0.054 | 7 | 13 |
| Nurbank | 0.049 | 6 | 0.049 | 7 | 13 |
| DO Temirbank | 0.079 | 9 | 0.079 | 10 | 19 |
| SB ABN Amro Bank | 0.043 | 5 | 0.043 | 6 | 11 |
| Bank CenterCredit | 0.058 | 7 | 0.058 | 8 | 15 |
| Eurasian Bank | 0.05 | 6 | 0.05 | 7 | 13 |
| Citibank Kazakhstan | 0.052 | 6 | 0.052 | 7 | 13 |
| Tsesnabank | 0.053 | 6 | 0.053 | 7 | 13 |
| SB HSBC Bank of Kazakhstan | 0.042 | 5 | 0.042 | 6 | 11 |
| ATF Bank | 0.047 | 5 | 0.047 | 6 | 11 |
| Halyk Bank of Kazakhstan | 0.057 | 7 | 0.057 | 7 | 14 |
| Bank Caspian | 0.06 | 7 | 0.06 | 8 | 15 |
| Kazkommertsbank | 0.053 | 6 | 0.053 | 7 | 13 |

### Appendix 3G: The Ranking Scores of the Assets Quality, 2008

| Banks | R6 | Rank | R7 | Rank | Total |
|---|---|---|---|---|---|
| Masterbank | 0 | 10 | 0 | 10 | 20 |
| SB Bank of China in Kazakhstan | 0 | 10 | 0 | 10 | 20 |
| Senim-Bank | 0 | 10 | 0 | 10 | 20 |
| SB Lariba-Bank | 0.013 | 10 | 0.011 | 10 | 20 |
| Zaman-Bank | 0.064 | 7 | 0.068 | 7 | 14 |
| TPBK | 0 | 10 | 0 | 10 | 20 |
| Express Bank | 0.008 | 10 | 0.009 | 10 | 20 |
| SB NB of Pakistan in Kazakhstan | 0 | 10 | 0 | 10 | 20 |
| SB Alfa-Bank | 0.013 | 10 | 0.034 | 9 | 19 |
| SB Taib Kazakh Bank | 0 | 10 | 0 | 10 | 20 |
| Kazinkombank | 0 | 10 | 0 | 10 | 20 |
| SB Sberbank of Russia | 0.039 | 8 | 0.036 | 8 | 16 |
| Delta Bank | 0.013 | 10 | 0.025 | 9 | 19 |
| Eximbank Kazakhstan | 0.005 | 10 | 0.013 | 10 | 20 |
| Metrokombank | 0 | 10 | 0 | 10 | 20 |
| MB Alma-Ata | 0.195 | 1 | 0.168 | 1 | 2 |
| Alliance Bank | 0.014 | 10 | 0.063 | 7 | 17 |
| Kazinvestbank | 0.002 | 10 | 0.005 | 10 | 20 |
| SB KZI bank | 0.003 | 10 | 0.004 | 10 | 20 |
| Demir Kazakhstan Bank | 0.009 | 10 | 0.015 | 10 | 20 |
| Danabank | 0.029 | 9 | 0.061 | 7 | 16 |
| Bank Turanalem | 0.006 | 10 | 0.025 | 9 | 19 |
| Nurbank | 0.023 | 9 | 0.075 | 6 | 15 |
| DO Temirbank | 0.026 | 9 | 0.131 | 3 | 12 |
| SB ABN Amro Bank | 0 | 10 | 0 | 10 | 20 |
| Bank CenterCredit | 0.01 | 10 | 0.059 | 7 | 17 |
| Eurasian Bank | 0.016 | 10 | 0.068 | 7 | 17 |
| Citibank Kazakhstan | 0.02 | 9 | 0.056 | 7 | 16 |
| Tsesnabank | 0.015 | 10 | 0.074 | 6 | 16 |
| SB HSBC Bank of Kazakhstan | 0 | 10 | 0 | 10 | 20 |
| ATF Bank | 0.01 | 10 | 0.061 | 7 | 17 |
| Halyk Bank of Kazakhstan | 0.019 | 10 | 0.117 | 4 | 14 |
| Bank Caspian | 0.034 | 9 | 0.178 | 1 | 10 |
| Kazkommertsbank | 0.022 | 9 | 0.137 | 3 | 12 |

## Appendix 3H: The Ranking Scores of the Liquidity and Leverage, 2008

| Banks | R15 | Rank | R4 | Rank | Total |
|---|---|---|---|---|---|
| Masterbank | 986.375 | 10 | 548.843 | 10 | 20 |
| SB Bank of China in Kazakhstan | 1.381 | 1 | 0.883 | 1 | 2 |
| Senim-Bank | 1.66 | 1 | 2.282 | 1 | 2 |
| SB Lariba-Bank | 0.717 | 1 | 1.593 | 1 | 2 |
| Zaman-Bank | 1.398 | 1 | 34.943 | 1 | 2 |
| TPBK | 0.938 | 1 | 0.591 | 1 | 2 |
| Express Bank | 1.762 | 1 | 6.014 | 1 | 2 |
| SB NB of Pakistan in Kazakhstan | 1.12 | 1 | 3.031 | 1 | 2 |
| SB Alfa-Bank | 0.504 | 1 | 0.366 | 1 | 2 |
| SB Taib Kazakh Bank | 1.38 | 1 | 1.764 | 1 | 2 |
| Kazinkombank | 0.957 | 1 | 4.895 | 1 | 2 |
| SB Sberbank of Russia | 1.736 | 1 | 1.5 | 1 | 2 |
| Delta Bank | 0.389 | 1 | 0.606 | 1 | 2 |
| Eximbank Kazakhstan | 0.595 | 1 | 0.436 | 1 | 2 |
| Metrokombank | 1.168 | 1 | 1.732 | 1 | 2 |
| MB Alma-Ata | 1.549 | 1 | 0.569 | 1 | 2 |
| Alliance Bank | 3.009 | 1 | 0.18 | 1 | 2 |
| Kazinvestbank | 1.108 | 1 | 0.245 | 1 | 2 |
| SB KZI bank | 0.938 | 1 | 0.461 | 1 | 2 |
| Demir Kazakhstan Bank | 0.744 | 1 | 0.491 | 1 | 2 |
| Danabank | 0.877 | 1 | 0.602 | 1 | 2 |
| Bank Turanalem | 1.485 | 1 | 0.211 | 1 | 2 |
| Nurbank | 1.61 | 1 | 0.275 | 1 | 2 |
| DO Temirbank | 1.558 | 1 | 0.199 | 1 | 2 |
| SB ABN Amro Bank | 1.302 | 1 | 0.179 | 1 | 2 |
| Bank CenterCredit | 1.297 | 1 | 0.133 | 1 | 2 |
| Eurasian Bank | 1.289 | 1 | 0.175 | 1 | 2 |
| Citibank Kazakhstan | 1.155 | 1 | 0.163 | 1 | 2 |
| Tsesnabank | 1.156 | 1 | 0.178 | 1 | 2 |
| SB HSBC Bank of Kazakhstan | 1.766 | 1 | 0.123 | 1 | 2 |
| ATF Bank | 1.594 | 1 | 0.142 | 1 | 2 |
| Halyk Bank of Kazakhstan | 1.192 | 1 | 0.123 | 1 | 2 |
| Bank Caspian | 1.38 | 1 | 0.161 | 1 | 2 |
| Kazkommertsbank | 1.35 | 1 | 0.146 | 1 | 2 |

## Appendix 3I: The Ranking Scores of the Capital Adequacy, 2014

| Banks | R1 | Rank | R2 | Rank | R3 | Rank | R5 | Rank | Total |
|---|---|---|---|---|---|---|---|---|---|
| SB PNB Kazakhstan | 0.836 | 10 | 0.816 | 10 | 1.097 | 10 | 0.197 | 10 | 40 |
| SB NB of Pakistan in Kazakhstan | 0.823 | 10 | 0.775 | 10 | 0.835 | 7 | 0.216 | 10 | 37 |
| Zaman Bank | 0.761 | 9 | 0.748 | 10 | 0.896 | 8 | 0.314 | 10 | 37 |
| SB KZI Bank | 0.672 | 8 | 0.62 | 8 | 0.718 | 6 | 0.488 | 10 | 32 |
| Islamic Bank Al Hilal | 0.640 | 8 | 0.617 | 8 | 0.999 | 9 | 0.562 | 10 | 35 |
| Shinhan Bank Kazakhstan | 0.641 | 8 | 0.615 | 8 | 1.19 | 10 | 0.559 | 10 | 36 |
| Home Credit Bank | 0.240 | 2 | 0.131 | 1 | 0.162 | 1 | 3.163 | 7 | 11 |
| Bank Positive Kazakhstan | 0.506 | 6 | 0.493 | 6 | 0.407 | 4 | 0.976 | 10 | 26 |
| SB Taib Kazakh Bank | 0.474 | 6 | 0.455 | 6 | 0.576 | 5 | 1.108 | 10 | 27 |
| SB RBS | 0.326 | 4 | 0.295 | 4 | 0.46 | 4 | 2.069 | 8 | 20 |
| Bank Kassa Nova | 0.190 | 2 | 0.122 | 1 | 0.166 | 1 | 4.276 | 6 | 10 |
| Eximbank Kazakhstan | 0.261 | 3 | 0.248 | 3 | 0.213 | 2 | 2.835 | 8 | 16 |
| ForteBank | 0.312 | 3 | 0.214 | 3 | 0.363 | 3 | 2.21 | 8 | 17 |
| AsiaCredit Bank | 0.209 | 2 | 0.191 | 2 | 0.199 | 2 | 3.791 | 7 | 13 |
| Kaspi Bank | 0.120 | 1 | 0.059 | 1 | 0.073 | 1 | 7.34 | 3 | 6 |
| Delta Bank | 0.117 | 1 | 0.095 | 1 | 0.128 | 1 | 7.55 | 3 | 6 |
| TPBK | 0.240 | 2 | 0.229 | 3 | 0.379 | 3 | 3.168 | 7 | 15 |
| Bank Astana-Finance | 0.152 | 1 | 0.144 | 2 | 0.221 | 2 | 5.599 | 5 | 10 |
| SB Alpha Bank | 0.162 | 1 | 0.101 | 1 | 0.098 | 1 | 5.181 | 5 | 8 |
| SB Bank of China | 0.159 | 1 | 0.141 | 2 | 0.555 | 5 | 5.281 | 5 | 13 |
| Eurasian Bank" | 0.134 | 1 | 0.072 | 1 | 0.086 | 1 | 6.491 | 4 | 7 |
| SB Sberbank | 0.128 | 1 | 0.08 | 1 | 0.079 | 1 | 6.842 | 3 | 6 |
| Kazkommertsbank | 0.179 | 2 | 0.122 | 1 | 0.126 | 1 | 4.596 | 6 | 10 |
| Halyk Bank of Kazakhstan | 0.153 | 1 | 0.095 | 1 | 0.112 | 1 | 5.548 | 5 | 8 |
| Citibank Kazakhstan | 0.155 | 1 | 0.149 | 2 | 0.206 | 2 | 5.435 | 5 | 10 |
| SB HSBC Bank Kazakhstan | 0.137 | 1 | 0.119 | 1 | 0.197 | 2 | 6.286 | 4 | 8 |
| VTB Bank Kazakhstan | 0.123 | 1 | 0.113 | 1 | 0.122 | 1 | 7.136 | 3 | 6 |
| Qazaq Banki | 0.110 | 1 | 0.107 | 1 | 0.177 | 1 | 8.084 | 2 | 5 |
| Bank RBK | 0.096 | 1 | 0.066 | 1 | 0.087 | 1 | 9.455 | 1 | 4 |
| Tsesnabank | 0.101 | 1 | 0.061 | 1 | 0.066 | 1 | 8.875 | 1 | 4 |
| Bank CenterCredit | 0.132 | 1 | 0.085 | 1 | 0.092 | 1 | 6.568 | 4 | 7 |
| Kazinvestbank | 0.123 | 1 | 0.087 | 1 | 0.1 | 1 | 7.124 | 3 | 6 |
| Temirbank | 0.143 | 1 | 0.076 | 1 | 0.09 | 1 | 6.007 | 4 | 7 |
| BTA Bank | 0.156 | 1 | 0.141 | 2 | 0.25 | 2 | 5.394 | 5 | 10 |
| ATF Bank | 0.098 | 1 | 0.092 | 1 | 0.122 | 1 | 9.161 | 1 | 4 |
| Nurbank | 0.173 | 2 | 0.151 | 2 | 0.184 | 2 | 4.787 | 6 | 12 |
| Alliance Bank | 0.103 | 1 | 0.075 | 1 | 0.109 | 1 | 8.685 | 1 | 4 |

**Appendix 3J: The Ranking Scores of the Return on Assets, 2014**

| Banks | R9 | Rank | R11 | Rank | Total |
|---|---|---|---|---|---|
| SB PNB Kazakhstan | 0.001 | 6 | 0.003 | 4 | 10 |
| SB NB of Pakistan in Kazakhstan | 0.046 | 8 | 0.057 | 6 | 14 |
| Zaman Bank | 0.013 | 7 | 0.023 | 5 | 12 |
| SB KZI Bank | 0.045 | 8 | 0.065 | 7 | 15 |
| Islamic Bank Al Hilal | 0.023 | 7 | 0.013 | 4 | 11 |
| Shinhan Bank Kazakhstan | 0.024 | 7 | 0.03 | 5 | 12 |
| Home Credit Bank | 0.105 | 10 | 0.076 | 7 | 17 |
| Bank Positive Kazakhstan | 0.01 | 6 | 0.022 | 5 | 11 |
| SB Taib Kazakh Bank | 0.013 | 7 | 0.002 | 4 | 11 |
| SB RBS | 0.025 | 7 | 0.037 | 5 | 12 |
| Bank Kassa Nova | 0.014 | 7 | 0.073 | 7 | 14 |
| Eximbank Kazakhstan | 0.004 | 6 | 0.05 | 6 | 12 |
| ForteBank | 0.022 | 7 | 0.032 | 5 | 12 |
| AsiaCredit Bank | 0.02 | 7 | 0.094 | 8 | 15 |
| Kaspi Bank | 0.038 | 8 | 0.114 | 9 | 17 |
| Delta Bank | 0.019 | 7 | 0.093 | 8 | 15 |
| TPBK | 0.01 | 6 | 0.013 | 4 | 10 |
| Bank Astana-Finance | 0.004 | 6 | 0.04 | 6 | 12 |
| SB Alpha Bank | 0.027 | 7 | 0.086 | 8 | 15 |
| SB Bank of China | 0.018 | 7 | 0.024 | 5 | 12 |
| Eurasian Bank" | 0.022 | 7 | 0.095 | 8 | 15 |
| SB Sberbank | 0.021 | 7 | 0.154 | 10 | 17 |
| Kazkommertsbank | 0.018 | 7 | 0.07 | 7 | 14 |
| Halyk Bank of Kazakhstan | 0.035 | 8 | 0.056 | 6 | 14 |
| Citibank Kazakhstan | 0.026 | 7 | 0.05 | 6 | 13 |
| SB HSBC Bank Kazakhstan | 0.022 | 7 | 0.047 | 6 | 13 |
| VTB Bank Kazakhstan | 0.004 | 6 | 0.052 | 6 | 12 |
| Qazaq Banki | 0.007 | 6 | 0.109 | 9 | 15 |
| Bank RBK | 0.007 | 6 | 0.093 | 8 | 14 |
| Tsesnabank | 0.018 | 7 | 0.082 | 7 | 14 |
| Bank CenterCredit | 0.002 | 6 | 0.046 | 6 | 12 |
| Kazinvestbank | 0.002 | 6 | 0.07 | 7 | 13 |
| Temirbank | 0.001 | 6 | 0.06 | 6 | 12 |
| BTA Bank | 0.018 | 7 | 0.079 | 7 | 14 |
| ATF Bank | 0 | 6 | 0.045 | 6 | 12 |
| Nurbank | -0.131 | 1 | -0.079 | 1 | 2 |
| Alliance Bank | 0.005 | 6 | 0.116 | 9 | 15 |

### Appendix 3K: The Ranking Scores of the Profitability, 2014

| Banks | R12 | Rank | R13 | Rank | Total |
|---|---|---|---|---|---|
| SB PNB Kazakhstan | 0.057 | 2 | 0.018 | 2 | 4 |
| SB NB of Pakistan in Kazakhstan | 0.108 | 4 | 0.058 | 4 | 8 |
| Zaman Bank | 0.064 | 2 | 0.027 | 3 | 5 |
| SB KZI Bank | 0.077 | 3 | 0.073 | 4 | 7 |
| Islamic Bank Al Hilal | 0.048 | 2 | 0.05 | 3 | 5 |
| Shinhan Bank Kazakhstan | 0.052 | 2 | 0.045 | 3 | 5 |
| Home Credit Bank | 0.269 | 10 | 0.214 | 10 | 20 |
| Bank Positive Kazakhstan | 0.067 | 3 | 0.054 | 4 | 7 |
| SB Taib Kazakh Bank | 0.057 | 2 | 0.049 | 3 | 5 |
| SB RBS | 0.017 | 1 | 0.016 | 2 | 3 |
| Bank Kassa Nova | 0.075 | 3 | 0.068 | 4 | 7 |
| Eximbank Kazakhstan | 0.08 | 3 | 0.056 | 4 | 7 |
| ForteBank | 0.041 | 2 | 0.036 | 3 | 5 |
| AsiaCredit Bank | 0.062 | 2 | 0.052 | 4 | 6 |
| Kaspi Bank | 0.087 | 3 | 0.064 | 4 | 7 |
| Delta Bank | 0.079 | 3 | 0.059 | 4 | 7 |
| TPBK | 0.02 | 1 | 0.018 | 2 | 3 |
| Bank Astana-Finance | 0.06 | 2 | 0.053 | 4 | 6 |
| SB Alpha Bank | 0.056 | 2 | 0.047 | 3 | 5 |
| SB Bank of China | 0.015 | 1 | 0.015 | 2 | 3 |
| Eurasian Bank" | 0.083 | 3 | 0.071 | 4 | 7 |
| SB Sberbank | 0.054 | 2 | 0.048 | 3 | 5 |
| Kazkommertsbank | 0.069 | 3 | 0.034 | 3 | 6 |
| Halyk Bank of Kazakhstan | 0.058 | 2 | 0.044 | 3 | 5 |
| Citibank Kazakhstan | 0.014 | 1 | 0.012 | 2 | 3 |
| SB HSBC Bank Kazakhstan | 0.036 | 1 | 0.035 | 3 | 4 |
| VTB Bank Kazakhstan | 0.067 | 3 | 0.059 | 4 | 7 |
| Qazaq Banki | 0.048 | 2 | 0.04 | 3 | 5 |
| Bank RBK | 0.057 | 2 | 0.052 | 4 | 6 |
| Tsesnabank | 0.055 | 2 | 0.051 | 4 | 6 |
| Bank CenterCredit | 0.05 | 2 | 0.037 | 3 | 5 |
| Kazinvestbank | 0.042 | 2 | 0.033 | 3 | 5 |
| Temirbank | 0.054 | 2 | 0.02 | 2 | 4 |
| BTA Bank | 0.057 | 2 | -0.02 | 1 | 3 |
| ATF Bank | 0.023 | 1 | 0.01 | 2 | 3 |
| Nurbank | 0.027 | 1 | 0.006 | 2 | 3 |
| Alliance Bank | 0.022 | 1 | -0.006 | 1 | 2 |

**Appendix 3L: The Ranking Scores of the Assets Quality, 2014**

| Banks | R6 | Rank | R7 | Rank | Total |
|---|---|---|---|---|---|
| SB PNB Kazakhstan | 0.157 | 9 | 0.1 | 10 | 19 |
| SB NB of Pakistan in Kazakhstan | 0.184 | 8 | 0.193 | 10 | 18 |
| Zaman Bank | 0.058 | 10 | 0.057 | 10 | 20 |
| SB KZI Bank | 0.035 | 10 | 0.034 | 10 | 20 |
| Islamic Bank Al Hilal | 0 | 10 | 0 | 10 | 20 |
| Shinhan Bank Kazakhstan | 0 | 10 | 0 | 10 | 20 |
| Home Credit Bank | 0.021 | 10 | 0.146 | 10 | 20 |
| Bank Positive Kazakhstan | 0.055 | 10 | 0.081 | 10 | 20 |
| SB Taib Kazakh Bank | 0.032 | 10 | 0.038 | 10 | 20 |
| SB RBS | 0 | 10 | 0 | 10 | 20 |
| Bank Kassa Nova | 0.009 | 10 | 0.047 | 10 | 20 |
| Eximbank Kazakhstan | 0.019 | 10 | 0.06 | 10 | 20 |
| ForteBank | 0.059 | 10 | 0.152 | 10 | 20 |
| AsiaCredit Bank | 0.037 | 10 | 0.116 | 10 | 20 |
| Kaspi Bank | 0.122 | 9 | 1.041 | 10 | 19 |
| Delta Bank | 0.008 | 10 | 0.059 | 10 | 20 |
| TPBK | 0 | 10 | 0 | 10 | 20 |
| Bank Astana-Finance | 0.068 | 10 | 0.262 | 10 | 20 |
| SB Alpha Bank | 0.011 | 10 | 0.056 | 10 | 20 |
| SB Bank of China | 0 | 10 | 0 | 10 | 20 |
| Eurasian Bank" | 0.089 | 9 | 0.675 | 10 | 19 |
| SB Sberbank | 0.074 | 10 | 0.283 | 10 | 20 |
| Kazkommertsbank | 0.294 | 7 | 1.982 | 10 | 17 |
| Halyk Bank of Kazakhstan | 0.163 | 9 | 0.776 | 10 | 19 |
| Citibank Kazakhstan | 0 | 10 | 0 | 10 | 20 |
| SB HSBC Bank Kazakhstan | 0.065 | 10 | 0.198 | 10 | 20 |
| VTB Bank Kazakhstan | 0.031 | 10 | 0.195 | 10 | 20 |
| Qazaq Banki | 0 | 10 | 0.001 | 10 | 20 |
| Bank RBK | 0.031 | 10 | 0.276 | 10 | 20 |
| Tsesnabank | 0.037 | 10 | 0.342 | 10 | 20 |
| Bank CenterCredit | 0.163 | 9 | 1.709 | 10 | 19 |
| Kazinvestbank | 0.139 | 9 | 0.963 | 10 | 19 |
| Temirbank | 0.402 | 6 | 1.681 | 10 | 16 |
| BTA Bank | 0.849 | 1 | 8.513 | 8 | 9 |
| ATF Bank | 0.423 | 6 | 4.343 | 9 | 15 |
| Nurbank | 0.293 | 7 | 1.327 | 10 | 17 |
| Alliance Bank | 0.498 | 5 | 29.001 | 1 | 19 |

**Appendix 3M: The Ranking Scores of the Liquidity and Leverage, 2014**

| Banks | R15 | Rank | R4 | Rank | Total |
|---|---|---|---|---|---|
| SB PNB Kazakhstan | 7.326 | 10 | 5.088 | 10 | 93 |
| SB NB of Pakistan in Kazakhstan | 2.83 | 4 | 4.636 | 10 | 91 |
| Zaman Bank | 2.945 | 4 | 3.189 | 7 | 85 |
| SB KZI Bank | 1.002 | 1 | 2.05 | 4 | 79 |
| Islamic Bank Al Hilal | 2.588 | 4 | 1.779 | 4 | 79 |
| Shinhan Bank Kazakhstan | 1.509 | 2 | 1.789 | 4 | 79 |
| Home Credit Bank | 3.833 | 5 | 0.316 | 1 | 74 |
| Bank Positive Kazakhstan | 0.524 | 1 | 1.025 | 2 | 67 |
| SB Taib Kazakh Bank | 1.52 | 2 | 0.903 | 2 | 67 |
| SB RBS | 1.483 | 2 | 0.483 | 1 | 58 |
| Bank Kassa Nova | 4.485 | 6 | 0.234 | 1 | 58 |
| Eximbank Kazakhstan | 0.409 | 1 | 0.353 | 1 | 57 |
| ForteBank | 0.978 | 1 | 0.453 | 1 | 56 |
| AsiaCredit Bank | 0.42 | 1 | 0.264 | 1 | 56 |
| Kaspi Bank | 2.266 | 3 | 0.136 | 1 | 53 |
| Delta Bank | 2.062 | 3 | 0.132 | 1 | 52 |
| TPBK | 0.755 | 1 | 0.316 | 1 | 50 |
| Bank Astana-Finance | 0.583 | 1 | 0.179 | 1 | 50 |
| SB Alpha Bank | 0.758 | 1 | 0.193 | 1 | 50 |
| SB Bank of China | 1.049 | 1 | 0.189 | 1 | 50 |
| Eurasian Bank" | 1.005 | 1 | 0.154 | 1 | 50 |
| SB Sberbank | 0.848 | 1 | 0.146 | 1 | 50 |
| Kazkommertsbank | 0.522 | 1 | 0.218 | 1 | 49 |
| Halyk Bank of Kazakhstan | 0.734 | 1 | 0.18 | 1 | 48 |
| Citibank Kazakhstan | 0.955 | 1 | 0.184 | 1 | 48 |
| SB HSBC Bank Kazakhstan | 0.977 | 1 | 0.159 | 1 | 47 |
| VTB Bank Kazakhstan | 0.948 | 1 | 0.14 | 1 | 47 |
| Qazaq Banki | 0.605 | 1 | 0.124 | 1 | 47 |
| Bank RBK | 0.851 | 1 | 0.106 | 1 | 46 |
| Tsesnabank | 0.731 | 1 | 0.113 | 1 | 46 |
| Bank CenterCredit | 0.456 | 1 | 0.152 | 1 | 45 |
| Kazinvestbank | 0.541 | 1 | 0.14 | 1 | 45 |
| Temirbank | 1.698 | 2 | 0.166 | 1 | 42 |
| BTA Bank | 1.448 | 2 | 0.185 | 1 | 39 |
| ATF Bank | 1.163 | 2 | 0.109 | 1 | 37 |
| Nurbank | 1.017 | 1 | 0.209 | 1 | 36 |
| Alliance Bank | 1.104 | 2 | 0.115 | 1 | 30 |

**Appendix 4A: Sample of Kazakhstan Banks for Altman Models from 1st January, 2008 to 1st January, 2014**

| | Bank | Year | Status | X1 | X2 | X3 | X4 |
|---|---|---|---|---|---|---|---|
| 1 | Bank Centercredit | 2008 | 0 | -0.644 | 0.016 | 0.058 | 0.133 |
| 2 | Bank RBK | 2008 | 0 | 0.566 | 0.013 | 0.007 | 4.895 |
| 3 | Halyk Bank of Kazakhstan | 2008 | 0 | -0.127 | 0.021 | 0.057 | 0.123 |
| 4 | Kaspi Bank | 2008 | 0 | -0.577 | 0.023 | 0.060 | 0.161 |
| 5 | SB Sberbank | 2008 | 0 | 0.451 | 0.021 | 0.046 | 1.500 |
| 6 | Tsesnabank | 2008 | 0 | -0.390 | 0.007 | 0.053 | 0.178 |
| 7 | Alliance Bank | 2008 | 1 | 0.051 | 0.031 | 0.078 | 0.180 |
| 8 | ATF Bank | 2008 | 1 | -0.360 | 0.006 | 0.047 | 0.142 |
| 9 | BTA Bank | 2008 | 1 | -0.525 | 0.018 | 0.054 | 0.211 |
| 10 | Kazkommertsbank | 2008 | 1 | 0.444 | 0.017 | 0.053 | 0.146 |
| 11 | Nurbank | 2008 | 1 | -0.164 | 0.015 | 0.049 | 0.275 |
| 12 | Temirbank | 2008 | 1 | 0.237 | 0.025 | 0.079 | 0.199 |
| 13 | Bank Centercredit | 2009 | 0 | -0.651 | 0.006 | 0.091 | 0.171 |
| 14 | Bank RBK | 2009 | 0 | 0.879 | 0.011 | 0.014 | 9.354 |
| 15 | Halyk Bank of Kazakhstan | 2009 | 0 | 0.068 | 0.006 | 0.072 | 0.143 |
| 16 | Kaspi Bank | 2009 | 0 | -0.807 | 0.005 | 0.097 | 0.173 |
| 17 | SB Sberbank | 2009 | 0 | 0.173 | 0.024 | 0.089 | 0.582 |
| 18 | Tsesnabank | 2009 | 0 | -0.580 | -0.043 | 0.042 | 0.157 |
| 19 | Alliance Bank | 2009 | 1 | 0.098 | 0.001 | 0.084 | 0.219 |
| 20 | ATF Bank | 2009 | 1 | -0.376 | -0.028 | 0.041 | 0.139 |
| 21 | BTA Bank | 2009 | 1 | -0.574 | 0.004 | 0.014 | 0.217 |
| 22 | Kazkommertsbank | 2009 | 1 | 0.425 | 0.000 | 0.076 | 0.167 |
| 23 | Nurbank | 2009 | 1 | -0.173 | 0.004 | 0.074 | 0.199 |
| 24 | Temirbank | 2009 | 1 | 0.342 | -0.006 | 0.336 | 0.226 |
| 25 | Bank Centercredit | 2010 | 0 | -0.626 | 0.001 | 0.071 | 0.145 |
| 26 | Bank RBK | 2010 | 0 | 1.158 | 0.009 | 0.001 | 5.469 |
| 27 | Halyk Bank of Kazakhstan | 2010 | 0 | -0.037 | 0.001 | 0.041 | 0.158 |
| 28 | Kaspi Bank | 2010 | 0 | -0.747 | 0.001 | 0.091 | 0.137 |
| 29 | SB Sberbank | 2010 | 0 | -0.077 | 0.010 | 0.048 | 0.207 |
| 30 | Tsesnabank | 2010 | 0 | -0.811 | 0.010 | 0.090 | 0.137 |
| 31 | Alliance Bank | 2010 | 1 | 0.122 | -1.133 | -1.062 | -0.458 |
| 32 | ATF Bank | 2010 | 1 | -0.405 | 0.001 | 0.055 | 0.156 |
| 33 | BTA Bank | 2010 | 1 | -0.548 | -1.067 | -0.887 | -0.504 |
| 34 | Kazkommertsbank | 2010 | 1 | 0.390 | 0.000 | 0.057 | 0.195 |
| 35 | Nurbank | 2010 | 1 | 0.035 | 0.003 | 0.067 | 0.207 |
| 36 | Temirbank | 2010 | 1 | 0.476 | -0.743 | -0.213 | -0.319 |
| 37 | Bank Centercredit | 2011 | 0 | -0.552 | -0.024 | 0.026 | 0.118 |
| 38 | Bank RBK | 2011 | 0 | -1.855 | 0.009 | 0.010 | 1.813 |

**Source:** Author

Continuation of Appendix 4A

| | Bank | Year | Status | X1 | X2 | X3 | X4 |
|---|---|---|---|---|---|---|---|
| 39 | Halyk Bank of Kazakhstan | 2011 | 0 | -0.068 | 0.014 | 0.057 | 0.169 |
| 40 | Kaspi Bank | 2011 | 0 | -0.800 | 0.012 | 0.098 | 0.159 |
| 41 | SB Sberbank | 2011 | 0 | -0.078 | 0.009 | 0.061 | 0.166 |
| 42 | Tsesnabank | 2011 | 0 | -1.258 | 0.003 | 0.094 | 0.129 |
| 43 | Alliance Bank | 2011 | 1 | 0.096 | 0.651 | 0.689 | 0.122 |
| 44 | ATF Bank | 2011 | 1 | -0.459 | -0.038 | 0.008 | 0.127 |
| 45 | BTA Bank | 2011 | 1 | -0.572 | 0.577 | 0.733 | 0.192 |
| 46 | Kazkommertsbank | 2011 | 1 | 0.350 | 0.000 | 0.055 | 0.187 |
| 47 | Nurbank | 2011 | 1 | -0.081 | -0.370 | -0.326 | 0.226 |
| 48 | Temirbank | 2011 | 1 | 0.401 | 0.390 | 0.457 | 0.163 |
| 49 | Bank Centercredit | 2012 | 0 | -0.679 | 0.003 | 0.053 | 0.147 |
| 50 | Bank RBK | 2012 | 0 | 0.017 | 0.001 | 0.062 | 0.164 |
| 51 | Halyk Bank of Kazakhstan | 2012 | 0 | -0.077 | 0.016 | 0.055 | 0.142 |
| 52 | Kaspi Bank | 2012 | 0 | -0.887 | 0.028 | 0.119 | 0.181 |
| 53 | SB Sberbank | 2012 | 0 | 0.006 | 0.016 | 0.073 | 0.132 |
| 54 | Tsesnabank | 2012 | 0 | -1.014 | 0.009 | 0.081 | 0.118 |
| 55 | Alliance Bank | 2012 | 1 | 0.120 | 0.021 | 0.096 | 0.144 |
| 56 | ATF Bank | 2012 | 1 | -0.415 | -0.038 | 0.004 | 0.132 |
| 57 | BTA Bank | 2012 | 1 | -0.589 | -0.015 | 0.072 | 0.231 |
| 58 | Kazkommertsbank | 2012 | 1 | 0.255 | 0.000 | 0.055 | 0.193 |
| 59 | Nurbank | 2012 | 1 | -0.104 | -0.004 | 0.040 | 0.217 |
| 60 | Temirbank | 2012 | 1 | 0.329 | 0.002 | 0.068 | 0.129 |
| 61 | Bank Centercredit | 2013 | 0 | -0.669 | 0.000 | 0.048 | 0.149 |
| 62 | Bank RBK | 2013 | 0 | -0.228 | 0.003 | 0.092 | 0.208 |
| 63 | Halyk Bank of Kazakhstan | 2013 | 0 | -0.018 | 0.025 | 0.065 | 0.141 |
| 64 | Kaspi Bank | 2013 | 0 | -0.892 | 0.032 | 0.125 | 0.173 |
| 65 | SB Sberbank | 2013 | 0 | 0.397 | 0.019 | 0.070 | 0.159 |
| 66 | Tsesnabank | 2013 | 0 | -0.962 | 0.017 | 0.090 | 0.128 |
| 67 | Alliance Bank | 2013 | 1 | -0.005 | 0.013 | 0.090 | 0.179 |
| 68 | ATF Bank | 2013 | 1 | -0.485 | -0.013 | 0.038 | 0.153 |
| 69 | BTA Bank | 2013 | 1 | -0.602 | -0.230 | -0.170 | 0.167 |
| 70 | Kazkommertsbank | 2013 | 1 | 0.225 | 0.001 | 0.047 | 0.180 |
| 71 | Nurbank | 2013 | 1 | -0.077 | -0.021 | 0.025 | 0.205 |
| 72 | Temirbank | 2013 | 1 | 0.241 | 0.050 | 0.109 | 0.139 |
| 73 | Bank Centercredit | 2014 | 0 | -0.328 | 0.002 | 0.046 | 0.152 |
| 74 | Bank RBK | 2014 | 0 | 0.265 | 0.007 | 0.093 | 0.106 |
| 75 | Halyk Bank of Kazakhstan | 2014 | 0 | -0.041 | 0.035 | 0.056 | 0.180 |
| 76 | Kaspi Bank | 2014 | 0 | -0.232 | 0.038 | 0.114 | 0.136 |
| 77 | SB Sberbank | 2014 | 0 | -0.325 | 0.021 | 0.154 | 0.146 |

**Source:** Author

Continuation of Appendix 4A

| | Bank | Year | Status | X1 | X2 | X3 | X4 |
|---|---|---|---|---|---|---|---|
| 78 | Tsesnabank | 2014 | 0 | 0.075 | 0.018 | 0.082 | 0.113 |
| 79 | Alliance Bank | 2014 | 1 | 0.255 | 0.005 | 0.116 | 0.115 |
| 80 | ATF Bank | 2014 | 1 | 0.025 | 0.000 | 0.045 | 0.109 |
| 81 | BTA Bank | 2014 | 1 | -0.197 | 0.018 | 0.079 | 0.185 |
| 82 | Kazkommertsbank | 2014 | 1 | -0.346 | 0.018 | 0.070 | 0.218 |
| 83 | Nurbank | 2014 | 1 | -0.296 | -0.131 | -0.079 | 0.209 |
| 84 | Temirbank | 2014 | 1 | -0.138 | 0.001 | 0.060 | 0.166 |

**Source:** Author

**Appendix 4B: Results of Classification by Altman Models for Banks from 2008 to 2014**

| Bank | Year | Assigned status | Z" | Predicted status | EM Score | Predicted status |
|---|---|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | -3.449 | 1 | -0.199 | 1 |
| Bank RBK | 2008 | 0 | 8.792 | 0 | 12.042 | 0 |
| Halyk Bank of Kazakhstan | 2008 | 0 | -0.214 | 1 | 3.036 | 0 |
| Kaspi Bank | 2008 | 0 | -2.964 | 1 | 0.286 | 1 |
| SB Sberbank | 2008 | 0 | 4.782 | 0 | 8.032 | 0 |
| Tsesnabank | 2008 | 0 | -1.875 | 1 | 1.375 | 1 |
| Alliance Bank | 2008 | 1 | 1.134 | 1 | 4.384 | 0 |
| ATF Bank | 2008 | 1 | -1.769 | 1 | 1.481 | 1 |
| BTA Bank | 2008 | 1 | -2.643 | 1 | 0.607 | 1 |
| Kazkommertsbank | 2008 | 1 | 3.345 | 0 | 6.595 | 0 |
| Nurbank | 2008 | 1 | -0.359 | 1 | 2.891 | 0 |
| Temirbank | 2008 | 1 | 2.306 | 1 | 5.556 | 0 |
| Bank Centercredit | 2009 | 0 | -3.264 | 1 | -0.014 | 1 |
| Bank RBK | 2009 | 0 | 15.492 | 0 | 18.742 | 0 |
| Halyk Bank of Kazakhstan | 2009 | 0 | 1.080 | 1 | 4.330 | 0 |
| Kaspi Bank | 2009 | 0 | -4.201 | 1 | -0.951 | 1 |
| SB Sberbank | 2009 | 0 | 2.373 | 1 | 5.623 | 0 |
| Tsesnabank | 2009 | 0 | -3.323 | 1 | -0.073 | 1 |
| Alliance Bank | 2009 | 1 | 1.412 | 1 | 4.662 | 0 |
| ATF Bank | 2009 | 1 | -2.023 | 1 | 1.227 | 1 |
| BTA Bank | 2009 | 1 | -3.257 | 1 | -0.007 | 1 |
| Kazkommertsbank | 2009 | 1 | 3.347 | 0 | 6.597 | 0 |
| Nurbank | 2009 | 1 | -0.363 | 1 | 2.887 | 0 |
| Temirbank | 2009 | 1 | 4.617 | 0 | 7.867 | 0 |
| Bank Centercredit | 2010 | 0 | -3.286 | 1 | -0.036 | 1 |
| Bank RBK | 2010 | 0 | 13.049 | 0 | 16.299 | 0 |
| Halyk Bank of Kazakhstan | 2010 | 0 | 0.214 | 1 | 3.464 | 0 |
| Kaspi Bank | 2010 | 0 | -3.917 | 1 | -0.667 | 1 |
| SB Sberbank | 2010 | 0 | 0.091 | 1 | 3.341 | 0 |
| Tsesnabank | 2010 | 0 | -4.295 | 1 | -1.045 | 1 |
| Alliance Bank | 2010 | 1 | -10.549 | 1 | -7.299 | 1 |
| ATF Bank | 2010 | 1 | -1.998 | 1 | 1.252 | 1 |
| BTA Bank | 2010 | 1 | -13.401 | 1 | -10.151 | 1 |
| Kazkommertsbank | 2010 | 1 | 3.030 | 0 | 6.280 | 0 |
| Nurbank | 2010 | 1 | 0.897 | 1 | 4.147 | 0 |
| Temirbank | 2010 | 1 | -1.210 | 1 | 2.040 | 1 |
| Bank Centercredit | 2011 | 0 | -3.235 | 1 | 0.015 | 1 |
| Bank RBK | 2011 | 0 | -9.605 | 1 | -6.355 | 1 |
| Halyk Bank of Kazakhstan | 2011 | 0 | 0.181 | 1 | 3.431 | 0 |
| Kaspi Bank | 2011 | 0 | -4.143 | 1 | -0.893 | 1 |
| SB Sberbank | 2011 | 0 | 0.126 | 1 | 3.376 | 0 |
| Tsesnabank | 2011 | 0 | -7.098 | 1 | -3.848 | 1 |

**Source:** Author

Continuation of Appendix 4B

| Bank | Year | Assigned status | Z" | Predicted status | EM Score | Predicted status |
|---|---|---|---|---|---|---|
| Alliance Bank | 2011 | 1 | 7.482 | 0 | 10.732 | 0 |
| ATF Bank | 2011 | 1 | -2.810 | 1 | 0.440 | 1 |
| BTA Bank | 2011 | 1 | 3.428 | 0 | 6.678 | 0 |
| Kazkommertsbank | 2011 | 1 | 2.758 | 0 | 6.008 | 0 |
| Nurbank | 2011 | 1 | -3.666 | 1 | -0.416 | 1 |
| Temirbank | 2011 | 1 | 7.025 | 0 | 10.275 | 0 |
| Bank Centercredit | 2012 | 0 | -3.730 | 1 | -0.480 | 1 |
| Bank RBK | 2012 | 0 | 0.699 | 1 | 3.949 | 0 |
| Halyk Bank of Kazakhstan | 2012 | 0 | 0.089 | 1 | 3.339 | 0 |
| Kaspi Bank | 2012 | 0 | -4.471 | 1 | -1.221 | 1 |
| SB Sberbank | 2012 | 0 | 0.719 | 1 | 3.969 | 0 |
| Tsesnabank | 2012 | 0 | -5.650 | 1 | -2.400 | 1 |
| Alliance Bank | 2012 | 1 | 1.617 | 1 | 4.867 | 0 |
| ATF Bank | 2012 | 1 | -2.556 | 1 | 0.694 | 1 |
| BTA Bank | 2012 | 1 | -3.009 | 1 | 0.241 | 1 |
| Kazkommertsbank | 2012 | 1 | 2.169 | 1 | 5.419 | 0 |
| Nurbank | 2012 | 1 | -0.167 | 1 | 3.083 | 0 |
| Temirbank | 2012 | 1 | 2.659 | 0 | 5.909 | 0 |
| Bank Centercredit | 2013 | 0 | -3.708 | 1 | -0.458 | 1 |
| Bank RBK | 2013 | 0 | -0.580 | 1 | 2.670 | 0 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.554 | 1 | 3.804 | 0 |
| Kaspi Bank | 2013 | 0 | -4.457 | 1 | -1.207 | 1 |
| SB Sberbank | 2013 | 0 | 3.185 | 0 | 6.435 | 0 |
| Tsesnabank | 2013 | 0 | -5.227 | 1 | -1.977 | 1 |
| Alliance Bank | 2013 | 1 | 0.805 | 1 | 4.055 | 0 |
| ATF Bank | 2013 | 1 | -2.662 | 1 | 0.588 | 1 |
| BTA Bank | 2013 | 1 | -5.485 | 1 | -2.235 | 1 |
| Kazkommertsbank | 2013 | 1 | 1.917 | 1 | 5.167 | 0 |
| Nurbank | 2013 | 1 | -0.166 | 1 | 3.084 | 0 |
| Temirbank | 2013 | 1 | 2.551 | 1 | 5.801 | 0 |
| Bank Centercredit | 2014 | 0 | -1.577 | 1 | 1.673 | 1 |
| Bank RBK | 2014 | 0 | 2.418 | 1 | 5.668 | 0 |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0.423 | 1 | 3.673 | 0 |
| Kaspi Bank | 2014 | 0 | -0.419 | 1 | 2.831 | 0 |
| SB Sberbank | 2014 | 0 | -0.777 | 1 | 2.473 | 1 |
| Tsesnabank | 2014 | 0 | 1.198 | 1 | 4.448 | 0 |
| Alliance Bank | 2014 | 1 | 2.513 | 1 | 5.763 | 0 |
| ATF Bank | 2014 | 1 | 0.574 | 1 | 3.824 | 0 |
| BTA Bank | 2014 | 1 | -0.449 | 1 | 2.801 | 0 |
| Kazkommertsbank | 2014 | 1 | -1.407 | 1 | 1.843 | 1 |
| Nurbank | 2014 | 1 | -2.591 | 1 | 0.659 | 1 |
| Temirbank | 2014 | 1 | -0.282 | 1 | 2.968 | 0 |

**Source:** Author

**Appendix 4C: Results of Classification by Altman Models for Banks from 2008 to 2014 with cutoff point at 93 percentile**

| Bank | Year | Assigned status | Z” | EM Score | Predicted status |
|---|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | -3.449 | -0.199 | 1 |
| Bank RBK | 2008 | 0 | 8.792 | 12.042 | 0 |
| Halyk Bank of Kazakhstan | 2008 | 0 | -0.214 | 3.036 | 1 |
| Kaspi Bank | 2008 | 0 | -2.964 | 0.286 | 1 |
| SB Sberbank | 2008 | 0 | 4.782 | 8.032 | 0 |
| Tsesnabank | 2008 | 0 | -1.875 | 1.375 | 1 |
| Alliance Bank | 2008 | 1 | 1.134 | 4.384 | 1 |
| ATF Bank | 2008 | 1 | -1.769 | 1.481 | 1 |
| BTA Bank | 2008 | 1 | -2.643 | 0.607 | 1 |
| Kazkommertsbank | 2008 | 1 | 3.345 | 6.595 | 1 |
| Nurbank | 2008 | 1 | -0.359 | 2.891 | 1 |
| Temirbank | 2008 | 1 | 2.306 | 5.556 | 1 |
| Bank Centercredit | 2009 | 0 | -3.264 | -0.014 | 1 |
| Bank RBK | 2009 | 0 | 15.492 | 18.742 | 0 |
| Halyk Bank of Kazakhstan | 2009 | 0 | 1.080 | 4.330 | 1 |
| Kaspi Bank | 2009 | 0 | -4.201 | -0.951 | 1 |
| SB Sberbank | 2009 | 0 | 2.373 | 5.623 | 1 |
| Tsesnabank | 2009 | 0 | -3.323 | -0.073 | 1 |
| Alliance Bank | 2009 | 1 | 1.412 | 4.662 | 1 |
| ATF Bank | 2009 | 1 | -2.023 | 1.227 | 1 |
| BTA Bank | 2009 | 1 | -3.257 | -0.007 | 1 |
| Kazkommertsbank | 2009 | 1 | 3.347 | 6.597 | 1 |
| Nurbank | 2009 | 1 | -0.363 | 2.887 | 1 |
| Temirbank | 2009 | 1 | 4.617 | 7.867 | 0 |
| Bank Centercredit | 2010 | 0 | -3.286 | -0.036 | 1 |
| Bank RBK | 2010 | 0 | 13.049 | 16.299 | 0 |
| Halyk Bank of Kazakhstan | 2010 | 0 | 0.214 | 3.464 | 1 |
| Kaspi Bank | 2010 | 0 | -3.917 | -0.667 | 1 |
| SB Sberbank | 2010 | 0 | 0.091 | 3.341 | 1 |
| Tsesnabank | 2010 | 0 | -4.295 | -1.045 | 1 |
| Alliance Bank | 2010 | 1 | -10.549 | -7.299 | 1 |
| ATF Bank | 2010 | 1 | -1.998 | 1.252 | 1 |
| BTA Bank | 2010 | 1 | -13.401 | -10.151 | 1 |
| Kazkommertsbank | 2010 | 1 | 3.030 | 6.280 | 1 |
| Nurbank | 2010 | 1 | 0.897 | 4.147 | 1 |
| Temirbank | 2010 | 1 | -1.210 | 2.040 | 1 |
| Bank Centercredit | 2011 | 0 | -3.235 | 0.015 | 1 |
| Bank RBK | 2011 | 0 | -9.605 | -6.355 | 1 |
| Halyk Bank of Kazakhstan | 2011 | 0 | 0.181 | 3.431 | 1 |
| Kaspi Bank | 2011 | 0 | -4.143 | -0.893 | 1 |

**Source:** Author

Continuation of Appendix 4C

| Bank | Year | Assigned status | Z" | EM Score | Predicted status |
|---|---|---|---|---|---|
| SB Sberbank | 2011 | 0 | 0.126 | 3.376 | 1 |
| Tsesnabank | 2011 | 0 | -7.098 | -3.848 | 1 |
| Alliance Bank | 2011 | 1 | 7.482 | 10.732 | 0 |
| ATF Bank | 2011 | 1 | -2.810 | 0.440 | 1 |
| BTA Bank | 2011 | 1 | 3.428 | 6.678 | 0 |
| Kazkommertsbank | 2011 | 1 | 2.758 | 6.008 | 1 |
| Nurbank | 2011 | 1 | -3.666 | -0.416 | 1 |
| Temirbank | 2011 | 1 | 7.025 | 10.275 | 0 |
| Bank Centercredit | 2012 | 0 | -3.730 | -0.480 | 1 |
| Bank RBK | 2012 | 0 | 0.699 | 3.949 | 1 |
| Halyk Bank of Kazakhstan | 2012 | 0 | 0.089 | 3.339 | 1 |
| Kaspi Bank | 2012 | 0 | -4.471 | -1.221 | 1 |
| SB Sberbank | 2012 | 0 | 0.719 | 3.969 | 1 |
| Tsesnabank | 2012 | 0 | -5.650 | -2.400 | 1 |
| Alliance Bank | 2012 | 1 | 1.617 | 4.867 | 1 |
| ATF Bank | 2012 | 1 | -2.556 | 0.694 | 1 |
| BTA Bank | 2012 | 1 | -3.009 | 0.241 | 1 |
| Kazkommertsbank | 2012 | 1 | 2.169 | 5.419 | 1 |
| Nurbank | 2012 | 1 | -0.167 | 3.083 | 1 |
| Temirbank | 2012 | 1 | 2.659 | 5.909 | 1 |
| Bank Centercredit | 2013 | 0 | -3.708 | -0.458 | 1 |
| Bank RBK | 2013 | 0 | -0.580 | 2.670 | 1 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.554 | 3.804 | 1 |
| Kaspi Bank | 2013 | 0 | -4.457 | -1.207 | 1 |
| SB Sberbank | 2013 | 0 | 3.185 | 6.435 | 1 |
| Tsesnabank | 2013 | 0 | -5.227 | -1.977 | 1 |
| Alliance Bank | 2013 | 1 | 0.805 | 4.055 | 1 |
| ATF Bank | 2013 | 1 | -2.662 | 0.588 | 1 |
| BTA Bank | 2013 | 1 | -5.485 | -2.235 | 1 |
| Kazkommertsbank | 2013 | 1 | 1.917 | 5.167 | 1 |
| Nurbank | 2013 | 1 | -0.166 | 3.084 | 1 |
| Temirbank | 2013 | 1 | 2.551 | 5.801 | 1 |
| Bank Centercredit | 2014 | 0 | -1.577 | 1.673 | 1 |
| Bank RBK | 2014 | 0 | 2.418 | 5.668 | 1 |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0.423 | 3.673 | 1 |
| Kaspi Bank | 2014 | 0 | -0.419 | 2.831 | 1 |
| SB Sberbank | 2014 | 0 | -0.777 | 2.473 | 1 |
| Tsesnabank | 2014 | 0 | 1.198 | 4.448 | 1 |
| Alliance Bank | 2014 | 1 | 2.513 | 5.763 | 1 |
| ATF Bank | 2014 | 1 | 0.574 | 3.824 | 1 |
| BTA Bank | 2014 | 1 | -0.449 | 2.801 | 1 |
| Kazkommertsbank | 2014 | 1 | -1.407 | 1.843 | 1 |
| Nurbank | 2014 | 1 | -2.591 | 0.659 | 1 |
| Temirbank | 2014 | 1 | -0.282 | 2.968 | 1 |

**Source:** Author

**Appendix 4D: Results of Classification by Re-estimated Altman Model Z"$_D$**

| Bank | Date | Assigned Status | Discriminant Scores | Predicted Status |
|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | 0.782 | 0 |
| Bank RBK | 2008 | 0 | 1.670 | 0 |
| Halyk Bank of Kazakhstan | 2008 | 0 | -0.223 | 1** |
| Kaspi Bank | 2008 | 0 | 0.682 | 0 |
| SB Sberbank | 2008 | 0 | -0.418 | 1** |
| Tsesnabank | 2008 | 0 | 0.301 | 0 |
| Alliance Bank | 2008 | 1 | -0.541 | 1 |
| ATF Bank | 2008 | 1 | 0.224 | 0** |
| BTA Bank | 2008 | 1 | 0.614 | 0** |
| Kazkommertsbank | 2008 | 1 | -1.332 | 1 |
| Nurbank | 2008 | 1 | -0.054 | 1 |
| Temirbank | 2008 | 1 | -0.911 | 1 |
| Bank Centercredit | 2009 | 0 | 0.747 | 0 |
| Bank RBK | 2009 | 0 | 4.027 | 0 |
| Halyk Bank of Kazakhstan | 2009 | 0 | -0.653 | 1** |
| Kaspi Bank | 2009 | 0 | 1.043 | 0 |
| SB Sberbank | 2009 | 0 | -0.547 | 1** |
| Tsesnabank | 2009 | 0 | 0.554 | 0 |
| Alliance Bank | 2009 | 1 | -0.690 | 1 |
| ATF Bank | 2009 | 1 | 0.179 | 0** |
| BTA Bank | 2009 | 1 | 0.740 | 0** |
| Kazkommertsbank | 2009 | 1 | -1.356 | 1 |
| Nurbank | 2009 | 1 | -0.151 | 1 |
| Temirbank | 2009 | 1 | -1.568 | 1 |
| Bank Centercredit | 2010 | 0 | 0.698 | 0 |
| Bank RBK | 2010 | 0 | 0.892 | 0 |
| Halyk Bank of Kazakhstan | 2010 | 0 | -0.400 | 1** |
| Kaspi Bank | 2010 | 0 | 0.900 | 0 |
| SB Sberbank | 2010 | 0 | -0.279 | 1** |
| Tsesnabank | 2010 | 0 | 1.048 | 0 |
| Alliance Bank | 2010 | 1 | -2.188 | 1 |
| ATF Bank | 2010 | 1 | 0.298 | 0** |
| BTA Bank | 2010 | 1 | -1.015 | 1 |
| Kazkommertsbank | 2010 | 1 | -1.241 | 1 |
| Nurbank | 2010 | 1 | -0.545 | 1 |
| Temirbank | 2010 | 1 | -3.143 | 1 |
| Bank Centercredit | 2011 | 0 | 0.543 | 0 |
| Bank RBK | 2011 | 0 | 4.338 | 0 |
| Halyk Bank of Kazakhstan | 2011 | 0 | -0.328 | 1** |
| Kaspi Bank | 2011 | 0 | 1.034 | 0 |
| SB Sberbank | 2011 | 0 | -0.325 | 1** |
| Tsesnabank | 2011 | 0 | 1.895 | 0 |
| Alliance Bank | 2011 | 1 | -0.099 | 1 |
| ATF Bank | 2011 | 1 | 0.360 | 0** |
| BTA Bank | 2011 | 1 | 1.008 | 0** |
| Kazkommertsbank | 2011 | 1 | -1.164 | 1 |
| Nurbank | 2011 | 1 | -0.608 | 1 |
| Temirbank | 2011 | 1 | -0.948 | 1 |
| Bank Centercredit | 2012 | 0 | 0.837 | 0 |
| Bank RBK | 2012 | 0 | -0.537 | 1** |

**Source:** Author

Continuation of Appendix 4D

| Bank | Date | Assigned Status | Discriminant Scores | Predicted Status |
|---|---|---|---|---|
| Halyk Bank of Kazakhstan | 2012 | 0 | -0.318 | 1** |
| Kaspi Bank | 2012 | 0 | 1.229 | 0 |
| SB Sberbank | 2012 | 0 | -0.515 | 1** |
| Tsesnabank | 2012 | 0 | 1.447 | 0 |
| Alliance Bank | 2012 | 1 | -0.754 | 1 |
| ATF Bank | 2012 | 1 | 0.286 | 0** |
| BTA Bank | 2012 | 1 | 0.646 | 0** |
| Kazkommertsbank | 2012 | 1 | -0.971 | 1 |
| Nurbank | 2012 | 1 | -0.240 | 1 |
| Temirbank | 2012 | 1 | -1.178 | 1 |
| Bank Centercredit | 2013 | 0 | 0.819 | 0 |
| Bank RBK | 2013 | 0 | -0.067 | 1** |
| Halyk Bank of Kazakhstan | 2013 | 0 | -0.430 | 1** |
| Kaspi Bank | 2013 | 0 | 1.230 | 0 |
| SB Sberbank | 2013 | 0 | -1.252 | 1** |
| Tsesnabank | 2013 | 0 | 1.356 | 0 |
| Alliance Bank | 2013 | 1 | -0.496 | 1 |
| ATF Bank | 2013 | 1 | 0.446 | 0** |
| BTA Bank | 2013 | 1 | 0.474 | 0** |
| Kazkommertsbank | 2013 | 1 | -0.909 | 1 |
| Nurbank | 2013 | 1 | -0.320 | 1 |
| Temirbank | 2013 | 1 | -0.944 | 1 |
| Bank Centercredit | 2014 | 0 | 0.161 | 0 |
| Bank RBK | 2014 | 0 | -1.094 | 1** |
| Halyk Bank of Kazakhstan | 2014 | 0 | -0.318 | 1** |
| Kaspi Bank | 2014 | 0 | -0.055 | 1** |
| SB Sberbank | 2014 | 0 | 0.031 | 0 |
| Tsesnabank | 2014 | 0 | -0.673 | 1** |
| Alliance Bank | 2014 | 1 | -1.107 | 1 |
| ATF Bank | 2014 | 1 | -0.564 | 1 |
| BTA Bank | 2014 | 1 | -0.086 | 1 |
| Kazkommertsbank | 2014 | 1 | 0.243 | 0** |
| Nurbank | 2014 | 1 | 0.005 | 0** |
| Temirbank | 2014 | 1 | -0.227 | 1 |

****misclassified cases**

**Source:** Author

**Appendix 4E: Results of Classification by Re-estimated Altman Model $Z''_W$**

| Bank | Date | Assigned Status | Discriminant Scores | Predicted Ststus |
|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | -0.740 | 0 |
| Bank RBK | 2008 | 0 | -1.717 | 0 |
| Halyk Bank of Kazakhstan | 2008 | 0 | 0.331 | 1** |
| Kaspi Bank | 2008 | 0 | -0.623 | 0 |
| SB Sberbank | 2008 | 0 | 0.518 | 1** |
| Tsesnabank | 2008 | 0 | -0.251 | 0 |
| Alliance Bank | 2008 | 1 | 0.656 | 1 |
| ATF Bank | 2008 | 1 | -0.161 | 0** |
| BTA Bank | 2008 | 1 | -0.552 | 0** |
| Kazkommertsbank | 2008 | 1 | 1.489 | 1 |
| Nurbank | 2008 | 1 | 0.145 | 1 |
| Temirbank | 2008 | 1 | 1.025 | 1 |
| Bank Centercredit | 2009 | 0 | -0.781 | 0 |
| Bank RBK | 2009 | 0 | -4.320 | 0 |
| Halyk Bank of Kazakhstan | 2009 | 0 | 0.719 | 1** |
| Kaspi Bank | 2009 | 0 | -1.105 | 0 |
| SB Sberbank | 2009 | 0 | 0.614 | 1** |
| Tsesnabank | 2009 | 0 | -0.625 | 0 |
| Alliance Bank | 2009 | 1 | 0.725 | 1 |
| ATF Bank | 2009 | 1 | -0.192 | 0** |
| BTA Bank | 2009 | 1 | -0.657 | 0** |
| Kazkommertsbank | 2009 | 1 | 1.436 | 1 |
| Nurbank | 2009 | 1 | 0.181 | 1 |
| Temirbank | 2009 | 1 | 1.221 | 1 |
| Bank Centercredit | 2010 | 0 | -0.710 | 0 |
| Bank RBK | 2010 | 0 | -0.917 | 0 |
| Halyk Bank of Kazakhstan | 2010 | 0 | 0.491 | 1** |
| Kaspi Bank | 2010 | 0 | -0.954 | 0 |
| SB Sberbank | 2010 | 0 | 0.374 | 1** |
| Tsesnabank | 2010 | 0 | -1.086 | 0 |
| Alliance Bank | 2010 | 1 | 1.267 | 1 |
| ATF Bank | 2010 | 1 | -0.264 | 0** |
| BTA Bank | 2010 | 1 | -0.079 | 0** |
| Kazkommertsbank | 2010 | 1 | 1.342 | 1 |
| Nurbank | 2010 | 1 | 0.603 | 1 |
| Temirbank | 2010 | 1 | 1.894 | 1 |
| Bank Centercredit | 2011 | 0 | -0.540 | 0 |
| Bank RBK | 2011 | 0 | -4.456 | 0 |
| Halyk Bank of Kazakhstan | 2011 | 0 | 0.420 | 1** |
| Kaspi Bank | 2011 | 0 | -1.080 | 0 |
| SB Sberbank | 2011 | 0 | 0.401 | 1** |
| Tsesnabank | 2011 | 0 | -2.000 | 0 |
| Alliance Bank | 2011 | 1 | 0.790 | 1 |
| ATF Bank | 2011 | 1 | -0.355 | 0** |
| BTA Bank | 2011 | 1 | -0.635 | 0** |
| Kazkommertsbank | 2011 | 1 | 1.266 | 1 |
| Nurbank | 2011 | 1 | 0.351 | 1 |
| Temirbank | 2011 | 1 | 1.387 | 1 |
| Bank Centercredit | 2012 | 0 | -0.823 | 0 |

**Source:** Author

Continuation of Appendix 4E

| Bank | Date | Assigned Status | Discriminant Scores | Predicted Ststus |
|---|---|---|---|---|
| Bank RBK | 2012 | 0 | 0.598 | 1** |
| Halyk Bank of Kazakhstan | 2012 | 0 | 0.421 | 1** |
| Kaspi Bank | 2012 | 0 | -1.275 | 0 |
| SB Sberbank | 2012 | 0 | 0.598 | 1** |
| Tsesnabank | 2012 | 0 | -1.491 | 0 |
| Alliance Bank | 2012 | 1 | 0.824 | 1 |
| ATF Bank | 2012 | 1 | -0.268 | 0** |
| BTA Bank | 2012 | 1 | -0.699 | 0** |
| Kazkommertsbank | 2012 | 1 | 1.065 | 1 |
| Nurbank | 2012 | 1 | 0.309 | 1 |
| Temirbank | 2012 | 1 | 1.266 | 1 |
| Bank Centercredit | 2013 | 0 | -0.802 | 0 |
| Bank RBK | 2013 | 0 | 0.062 | 1** |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.543 | 1** |
| Kaspi Bank | 2013 | 0 | -1.278 | 0 |
| SB Sberbank | 2013 | 0 | 1.383 | 1** |
| Tsesnabank | 2013 | 0 | -1.390 | 0 |
| Alliance Bank | 2013 | 1 | 0.541 | 1 |
| ATF Bank | 2013 | 1 | -0.428 | 0** |
| BTA Bank | 2013 | 1 | -0.678 | 0** |
| Kazkommertsbank | 2013 | 1 | 1.013 | 1 |
| Nurbank | 2013 | 1 | 0.375 | 1 |
| Temirbank | 2013 | 1 | 1.078 | 1 |
| Bank Centercredit | 2014 | 0 | -0.104 | 0 |
| Bank RBK | 2014 | 0 | 1.151 | 1** |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0.466 | 1** |
| Kaspi Bank | 2014 | 0 | 0.105 | 1** |
| SB Sberbank | 2014 | 0 | -0.094 | 0 |
| Tsesnabank | 2014 | 0 | 0.755 | 1** |
| Alliance Bank | 2014 | 1 | 1.122 | 1 |
| ATF Bank | 2014 | 1 | 0.654 | 1 |
| BTA Bank | 2014 | 1 | 0.142 | 1 |
| Kazkommertsbank | 2014 | 1 | -0.189 | 0** |
| Nurbank | 2014 | 1 | -0.079 | 0** |
| Temirbank | 2014 | 1 | 0.276 | 1 |

**misclassified cases

**Source:** Author

**Appendix 4F: Results of Classification by Re-estimated Altman Models Z”$_D$ and Z”$_W$ with New Cutoff Points**

| Bank | Year | Assigned Status | Z”$_D$ Discriminant Scores | Predicted Status | Z”$_W$ Discriminant Scores | Predicted Status |
|---|---|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | 0.782 | 0 | -0.740 | 0 |
| Bank RBK | 2008 | 0 | 1.670 | 0 | -1.717 | 0 |
| Halyk Bank of Kazakhstan | 2008 | 0 | -0.223 | 1 | 0.331 | 1 |
| Kaspi Bank | 2008 | 0 | 0.682 | 0 | -0.623 | 0 |
| SB Sberbank | 2008 | 0 | -0.418 | 1 | 0.518 | 1 |
| Tsesnabank | 2008 | 0 | 0.301 | 1 | -0.251 | 1 |
| Alliance Bank | 2008 | 1 | -0.541 | 1 | 0.656 | 1 |
| ATF Bank | 2008 | 1 | 0.224 | 1 | -0.161 | 1 |
| BTA Bank | 2008 | 1 | 0.614 | 1 | -0.552 | 1 |
| Kazkommertsbank | 2008 | 1 | -1.332 | 1 | 1.489 | 1 |
| Nurbank | 2008 | 1 | -0.054 | 1 | 0.145 | 1 |
| Temirbank | 2008 | 1 | -0.911 | 1 | 1.025 | 1 |
| Bank Centercredit | 2009 | 0 | 0.747 | 0 | -0.781 | 0 |
| Bank RBK | 2009 | 0 | 4.027 | 0 | -4.320 | 0 |
| Halyk Bank of Kazakhstan | 2009 | 0 | -0.653 | 1 | 0.719 | 1 |
| Kaspi Bank | 2009 | 0 | 1.043 | 0 | -1.105 | 0 |
| SB Sberbank | 2009 | 0 | -0.547 | 1 | 0.614 | 1 |
| Tsesnabank | 2009 | 0 | 0.554 | 1 | -0.625 | 0 |
| Alliance Bank | 2009 | 1 | -0.690 | 1 | 0.725 | 1 |
| ATF Bank | 2009 | 1 | 0.179 | 1 | -0.192 | 1 |
| BTA Bank | 2009 | 1 | 0.740 | 0 | -0.657 | 0 |
| Kazkommertsbank | 2009 | 1 | -1.356 | 1 | 1.436 | 1 |
| Nurbank | 2009 | 1 | -0.151 | 1 | 0.181 | 1 |
| Temirbank | 2009 | 1 | -1.568 | 1 | 1.221 | 1 |
| Bank Centercredit | 2010 | 0 | 0.698 | 0 | -0.710 | 0 |
| Bank RBK | 2010 | 0 | 0.892 | 0 | -0.917 | 0 |
| Halyk Bank of Kazakhstan | 2010 | 0 | -0.400 | 1 | 0.491 | 1 |
| Kaspi Bank | 2010 | 0 | 0.900 | 0 | -0.954 | 0 |
| SB Sberbank | 2010 | 0 | -0.279 | 1 | 0.374 | 1 |
| Tsesnabank | 2010 | 0 | 1.048 | 0 | -1.086 | 0 |
| Alliance Bank | 2010 | 1 | -2.188 | 1 | 1.267 | 1 |
| ATF Bank | 2010 | 1 | 0.298 | 1 | -0.264 | 1 |
| BTA Bank | 2010 | 1 | -1.015 | 1 | -0.079 | 1 |
| Kazkommertsbank | 2010 | 1 | -1.241 | 1 | 1.342 | 1 |
| Nurbank | 2010 | 1 | -0.545 | 1 | 0.603 | 1 |
| Temirbank | 2010 | 1 | -3.143 | 1 | 1.894 | 1 |
| Bank Centercredit | 2011 | 0 | 0.543 | 1 | -0.540 | 1 |
| Bank RBK | 2011 | 0 | 4.338 | 0 | -4.456 | 0 |
| Halyk Bank of Kazakhstan | 2011 | 0 | -0.328 | 1 | 0.420 | 1 |
| Kaspi Bank | 2011 | 0 | 1.034 | 0 | -1.080 | 0 |
| SB Sberbank | 2011 | 0 | -0.325 | 1 | 0.401 | 1 |

**Source:** Author

Continuation of Appendix 4F

| Bank | Year | Assigned Status | Z”$_D$ Discriminant Scores | Predicted Status | Z”$_W$ Discriminant Scores | Predicted Status |
|---|---|---|---|---|---|---|
| Tsesnabank | 2011 | 0 | 1.895 | 0 | -2.000 | 0 |
| Alliance Bank | 2011 | 1 | -0.099 | 1 | 0.790 | 1 |
| ATF Bank | 2011 | 1 | 0.360 | 1 | -0.355 | 1 |
| BTA Bank | 2011 | 1 | 1.008 | 0 | -0.635 | 0 |
| Kazkommertsbank | 2011 | 1 | -1.164 | 1 | 1.266 | 1 |
| Nurbank | 2011 | 1 | -0.608 | 1 | 0.351 | 1 |
| Temirbank | 2011 | 1 | -0.948 | 1 | 1.387 | 1 |
| Bank Centercredit | 2012 | 0 | 0.837 | 0 | -0.823 | 0 |
| Bank RBK | 2012 | 0 | -0.537 | 1 | 0.598 | 1 |
| Halyk Bank of Kazakhstan | 2012 | 0 | -0.318 | 1 | 0.421 | 1 |
| Kaspi Bank | 2012 | 0 | 1.229 | 0 | -1.275 | 0 |
| SB Sberbank | 2012 | 0 | -0.515 | 1 | 0.598 | 1 |
| Tsesnabank | 2012 | 0 | 1.447 | 0 | -1.491 | 0 |
| Alliance Bank | 2012 | 1 | -0.754 | 1 | 0.824 | 1 |
| ATF Bank | 2012 | 1 | 0.286 | 1 | -0.268 | 1 |
| BTA Bank | 2012 | 1 | 0.646 | 1 | -0.699 | 0 |
| Kazkommertsbank | 2012 | 1 | -0.971 | 1 | 1.065 | 1 |
| Nurbank | 2012 | 1 | -0.240 | 1 | 0.309 | 1 |
| Temirbank | 2012 | 1 | -1.178 | 1 | 1.266 | 1 |
| Bank Centercredit | 2013 | 0 | 0.819 | 0 | -0.802 | 0 |
| Bank RBK | 2013 | 0 | -0.067 | 1 | 0.062 | 1 |
| Halyk Bank of Kazakhstan | 2013 | 0 | -0.430 | 1 | 0.543 | 1 |
| Kaspi Bank | 2013 | 0 | 1.230 | 0 | -1.278 | 0 |
| SB Sberbank | 2013 | 0 | -1.252 | 1 | 1.383 | 1 |
| Tsesnabank | 2013 | 0 | 1.356 | 0 | -1.390 | 0 |
| Alliance Bank | 2013 | 1 | -0.496 | 1 | 0.541 | 1 |
| ATF Bank | 2013 | 1 | 0.446 | 1 | -0.428 | 1 |
| BTA Bank | 2013 | 1 | 0.474 | 1 | -0.678 | 0 |
| Kazkommertsbank | 2013 | 1 | -0.909 | 1 | 1.013 | 1 |
| Nurbank | 2013 | 1 | -0.320 | 1 | 0.375 | 1 |
| Temirbank | 2013 | 1 | -0.944 | 1 | 1.078 | 1 |
| Bank Centercredit | 2014 | 0 | 0.161 | 1 | -0.104 | 1 |
| Bank RBK | 2014 | 0 | -1.094 | 1 | 1.151 | 1 |
| Halyk Bank of Kazakhstan | 2014 | 0 | -0.318 | 1 | 0.466 | 1 |
| Kaspi Bank | 2014 | 0 | -0.055 | 1 | 0.105 | 1 |
| SB Sberbank | 2014 | 0 | 0.031 | 1 | -0.094 | 1 |
| Tsesnabank | 2014 | 0 | -0.673 | 1 | 0.755 | 1 |
| Alliance Bank | 2014 | 1 | -1.107 | 1 | 1.122 | 1 |
| ATF Bank | 2014 | 1 | -0.564 | 1 | 0.654 | 1 |
| BTA Bank | 2014 | 1 | -0.086 | 1 | 0.142 | 1 |
| Kazkommertsbank | 2014 | 1 | 0.243 | 1 | -0.189 | 1 |
| Nurbank | 2014 | 1 | 0.005 | 1 | -0.079 | 1 |
| Temirbank | 2014 | 1 | -0.227 | 1 | 0.276 | 1 |

**Source:** Author

Appendix 5A

Data for MDA, Logit and Probit Analyses (in sample)

| Banks | Year | Status | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bank Centercredit | 2008 | 0 | 0,122 | 0.073 | 0.128 | 0.133 | 7.529 | 0.01 | 0.059 | 0.008 | 0.016 | 0.128 | 0.058 | 0.026 | 0.024 | -0.644 | 1.297 |
| Bank RBK | 2008 | 0 | 0.83 | 0.689 | 0.868 | 4.895 | 0.204 | 0 | 0 | 0.044 | 0.013 | 0.015 | 0.007 | 0.088 | 0.088 | 0.566 | 0.957 |
| Halyk Bank of Kazakhstan | 2008 | 0 | 0.112 | 0.07 | 0.12 | 0.123 | 8.151 | 0.019 | 0.117 | 0.01 | 0.021 | 0.187 | 0.057 | 0.031 | 0.028 | -0.127 | 1.192 |
| Kaspi Bank | 2008 | 0 | 0.142 | 0.089 | 0.128 | 0.161 | 6.222 | 0.034 | 0.178 | 0.019 | 0.023 | 0.159 | 0.06 | 0.068 | 0.063 | -0.577 | 1.38 |
| SB Sberbank | 2008 | 0 | 0.636 | 0.496 | 0.482 | 1.5 | 0.667 | 0.039 | 0.036 | 0.021 | 0.021 | 0.034 | 0.046 | 0.046 | 0.038 | 0.451 | 1.736 |
| Tsesnabank | 2008 | 0 | 0.155 | 0.112 | 0.14 | 0.178 | 5.626 | 0.015 | 0.074 | 0.021 | 0.007 | 0.045 | 0.053 | 0.025 | 0.022 | -0.39 | 1.156 |
| Alliance Bank | 2008 | 1 | 0.156 | 0.113 | 0.143 | 0.18 | 5.557 | 0.014 | 0.063 | 0.008 | 0.031 | 0.2 | 0.078 | 0.048 | 0.045 | 0.051 | 3.009 |
| ATF Bank | 2008 | 1 | 0.131 | 0.085 | 0.142 | 0.142 | 7.033 | 0.01 | 0.061 | 0.006 | 0.006 | 0.047 | 0.047 | 0.02 | 0.018 | -0.36 | 1.594 |
| BTA Bank | 2008 | 1 | 0.179 | 0.136 | 0.138 | 0.211 | 4.732 | 0.006 | 0.025 | 0.006 | 0.018 | 0.103 | 0.054 | 0.023 | 0.02 | -0.525 | 1.485 |
| Kazkommertsbank | 2008 | 1 | 0.132 | 0.083 | 0.123 | 0.146 | 6.827 | 0.022 | 0.137 | 0.004 | 0.017 | 0.129 | 0.053 | 0.028 | 0.025 | 0.444 | 1.35 |
| Nurbank | 2008 | 1 | 0.223 | 0.173 | 0.209 | 0.275 | 3.636 | 0.023 | 0.075 | 0 | 0.015 | 0.067 | 0.049 | 0.016 | 0.011 | -0.164 | 1.61 |
| Temirbank | 2008 | 1 | 0.166 | 0.141 | 0.141 | 0.199 | 5.024 | 0.026 | 0.131 | 0.013 | 0.025 | 0.149 | 0.079 | 0.039 | 0.034 | 0.237 | 1.558 |
| Bank Centercredit | 2009 | 0 | 0.154 | 0.103 | 0.186 | 0.171 | 5.863 | 0.024 | 0.108 | 0.01 | 0.006 | 0.066 | 0.091 | 0.026 | 0.025 | -0.651 | 0.295 |
| Bank RBK | 2009 | 0 | 0.903 | 0.744 | 0.911 | 9.354 | 0.107 | 0 | 0 | 0.082 | 0.011 | 0.012 | 0.014 | 0.088 | 0.087 | 0.879 | 6.096 |
| Halyk Bank of Kazakhstan | 2009 | 0 | 0.128 | 0.086 | 0.123 | 0.143 | 7.017 | 0.043 | 0.256 | 0.009 | 0.006 | 0.058 | 0.072 | 0.029 | 0.028 | 0.068 | 1.274 |
| Kaspi Bank | 2009 | 0 | 0.152 | 0.113 | 0.141 | 0.173 | 5.781 | 0.046 | 0.226 | 0.018 | 0.005 | 0.042 | 0.097 | 0.055 | 0.052 | -0.807 | 0.13 |
| SB Sberbank | 2009 | 0 | 0.378 | 0.327 | 0.41 | 0.582 | 1.717 | 0.045 | 0.094 | 0.021 | 0.024 | 0.068 | 0.089 | 0.048 | 0.038 | 0.173 | 1.108 |
| Tsesnabank | 2009 | 0 | 0.139 | 0.1 | 0.129 | 0.157 | 6.387 | 0.041 | 0.194 | 0.023 | -0.043 | -0.378 | 0.042 | 0.024 | 0.022 | -0.58 | 0.393 |
| Alliance Bank | 2009 | 1 | 0.185 | 0.166 | 0.193 | 0.219 | 4.572 | 0.033 | 0.12 | 0.009 | 0.001 | 0.01 | 0.084 | 0.042 | 0.038 | 0.098 | 1.577 |
| ATF Bank | 2009 | 1 | 0.128 | 0.09 | 0.129 | 0.139 | 7.196 | 0.054 | 0.341 | 0.007 | -0.028 | -0.373 | 0.041 | 0.023 | 0.022 | -0.376 | 0.358 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTA Bank | 2009 | 1 | 0.186 | 0.139 | 0.132 | 0.217 | 4.615 | 0.042 | 0.18 | 0.005 | 0.004 | 0.03 | 0.014 | 0.031 | 0.028 | -0.574 | 0.119 |
| Kazkommertsbank | 2009 | 1 | 0.153 | 0.11 | 0.133 | 0.167 | 6.003 | 0.059 | 0.356 | 0.004 | 0 | 0.005 | 0.076 | 0.045 | 0.042 | 0.425 | 1.653 |
| Nurbank | 2009 | 1 | 0.169 | 0.147 | 0.155 | 0.199 | 5.023 | 0.031 | 0.152 | 0.011 | 0.004 | 0.024 | 0.074 | 0.024 | 0.018 | -0.173 | 0.306 |
| Temirbank | 2009 | 1 | 0.185 | 0.182 | 0.149 | 0.226 | 4.425 | 0.042 | 0.202 | 0.013 | -0.006 | -0.033 | 0.336 | 0.024 | 0.016 | 0.342 | 1.815 |
| Bank Centercredit | 2010 | 0 | 0.134 | 0.088 | 0.129 | 0.145 | 6.906 | 0.042 | 0.181 | 0.015 | 0.001 | 0.017 | 0.071 | 0.059 | 0.047 | -0.626 | 1.953 |
| Bank RBK | 2010 | 0 | 0.851 | 0.722 | 0.785 | 5.469 | 0.183 | 0.002 | 0.002 | 0.004 | 0.009 | 0.01 | 0.001 | 0.16 | 0.155 | 1.158 | 1.358 |
| Halyk Bank of Kazakhstan | 2010 | 0 | 0.139 | 0.111 | 0.143 | 0.158 | 6.34 | 0.082 | 0.367 | 0.01 | 0.001 | 0.011 | 0.041 | 0.049 | 0.039 | -0.037 | 0.842 |
| Kaspi Bank | 2010 | 0 | 0.122 | 0.099 | 0.105 | 0.137 | 7.326 | 0.061 | 0.414 | 0.006 | 0.001 | 0.011 | 0.091 | 0.066 | 0.054 | -0.747 | 1.336 |
| SB Sberbank | 2010 | 0 | 0.173 | 0.155 | 0.248 | 0.207 | 4.83 | 0.06 | 0.151 | 0.015 | 0.01 | 0.062 | 0.048 | 0.057 | 0.044 | -0.077 | 1.713 |
| Tsesnabank | 2010 | 0 | 0.123 | 0.092 | 0.094 | 0.137 | 7.313 | 0.033 | 0.198 | 0.008 | 0.01 | 0.096 | 0.09 | 0.062 | 0.053 | -0.811 | 0.732 |
| Alliance Bank | 2010 | 1 | -0.841 | -0.841 | -0.451 | -0.458 | -2.184 | 0.708 | -0.798 | 0.043 | -1.133 | 1.353 | -1.062 | 0.006 | 0.004 | 0.122 | 1.39 |
| ATF Bank | 2010 | 1 | 0.142 | 0.102 | 0.151 | 0.156 | 6.4 | 0.096 | 0.53 | 0.017 | 0.001 | 0.015 | 0.055 | 0.043 | 0.032 | -0.405 | 1.985 |
| BTA Bank | 2010 | 1 | -0.881 | -0.966 | -0.673 | -0.504 | -1.983 | 0.759 | -1.103 | 0.015 | -1.067 | 1.427 | -0.887 | -0.019 | -0.018 | -0.548 | 0.535 |
| Kazkommertsbank | 2010 | 1 | 0.173 | 0.128 | 0.11 | 0.195 | 5.124 | 0.12 | 0.685 | 0.005 | 0 | 0 | 0.057 | 0.095 | 0.062 | 0.39 | 0.588 |
| Nurbank | 2010 | 1 | 0.176 | 0.147 | 0.144 | 0.207 | 4.823 | 0.019 | 0.085 | 0.009 | 0.003 | 0.017 | 0.067 | 0.044 | 0.031 | 0.035 | 0.567 |
| Temirbank | 2010 | 1 | -0.468 | -0.469 | -0.304 | -0.319 | -3.131 | 0.473 | -1.479 | 0.013 | -0.743 | 1.595 | -0.213 | -0.006 | -0.022 | 0.476 | 0.983 |
| Bank Centercredit | 2011 | 0 | 0.111 | 0.073 | 0.106 | 0.118 | 8.439 | 0.087 | 0.465 | 0.007 | -0.024 | -0.218 | 0.026 | 0.011 | 0.011 | -0.552 | 1.469 |
| Bank RBK | 2011 | 0 | 0.644 | 0.589 | 0.689 | 1.813 | 0.552 | 0.002 | 0.002 | 0.014 | 0.009 | 0.013 | 0.01 | 0.119 | 0.008 | -1.855 | 1.853 |
| Halyk Bank of Kazakhstan | 2011 | 0 | 0.147 | 0.109 | 0.135 | 0.169 | 5.92 | 0.126 | 0.519 | 0.006 | 0.014 | 0.092 | 0.057 | 0.052 | 0.039 | -0.068 | 1.101 |
| Kaspi Bank | 2011 | 0 | 0.143 | 0.085 | 0.094 | 0.159 | 6.296 | 0.088 | 0.504 | 0.015 | 0.012 | 0.084 | 0.098 | 0.089 | 0.071 | -0.8 | 1.051 |
| SB Sberbank | 2011 | 0 | 0.143 | 0.129 | 0.155 | 0.166 | 6.01 | 0.05 | 0.219 | 0.013 | 0.009 | 0.064 | 0.061 | 0.053 | 0.051 | -0.078 | 0.661 |
| Tsesnabank | 2011 | 0 | 0.116 | 0.101 | 0.107 | 0.129 | 7.749 | 0.033 | 0.186 | 0.01 | 0.003 | 0.023 | 0.094 | 0.042 | 0.049 | -1.258 | 0.701 |
| Alliance Bank | 2011 | 1 | 0.114 | 0.089 | 0.109 | 0.122 | 8.187 | 0.508 | 4.98 | 0.015 | 0.651 | 5.73 | 0.689 | 0.016 | -0.006 | 0.096 | 1.681 |
| ATF Bank | 2011 | 1 | 0.119 | 0.077 | 0.089 | 0.127 | 7.872 | 0.121 | 0.878 | 0.006 | -0.038 | -0.323 | 0.008 | 0.026 | 0.023 | -0.459 | 0.79 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTA Bank | 2011 | 1 | 0.174 | 0.138 | 0.15 | 0.192 | 5.21 | 0.423 | 2.001 | 0.007 | 0.577 | 3.306 | 0.733 | -0.044 | -0.034 | -0.572 | 1.437 |
| Kazkommertsbank | 2011 | 1 | 0.166 | 0.123 | 0.111 | 0.187 | 5.342 | 0.123 | 0.717 | 0.004 | 0 | 0 | 0.055 | 0.066 | 0.038 | 0.35 | 0.675 |
| Nurbank | 2011 | 1 | 0.188 | 0.164 | 0.2 | 0.226 | 4.42 | 0.304 | 1.241 | 0.011 | -0.37 | -1.965 | -0.326 | 0.033 | 0.009 | -0.081 | 0.797 |
| Temirbank | 2011 | 1 | 0.15 | 0.081 | 0.09 | 0.163 | 6.121 | 0.47 | 3.461 | 0.015 | 0.39 | 2.601 | 0.457 | 0.022 | -0.016 | 0.401 | 3.732 |
| Bank Centercredit | 2012 | 0 | 0.128 | 0.083 | 0.094 | 0.147 | 6.787 | 0.089 | 0.524 | 0.007 | 0.003 | 0.038 | 0.053 | 0.023 | 0.016 | -0.679 | 0.796 |
| Bank RBK | 2012 | 0 | 0.141 | 0.133 | 0.177 | 0.164 | 6.111 | 0.002 | 0.008 | 0.014 | 0.001 | 0.004 | 0.062 | 0.061 | 0.054 | 0.017 | 1.628 |
| Halyk Bank of Kazakhstan | 2012 | 0 | 0.125 | 0.092 | 0.119 | 0.142 | 7.028 | 0.15 | 0.744 | 0.006 | 0.016 | 0.126 | 0.055 | 0.045 | 0.032 | -0.077 | 0.895 |
| Kaspi Bank | 2012 | 0 | 0.153 | 0.081 | 0.088 | 0.181 | 5.533 | 0.065 | 0.363 | 0.015 | 0.028 | 0.256 | 0.119 | 0.099 | 0.075 | -0.887 | 1.513 |
| SB Sberbank | 2012 | 0 | 0.117 | 0.08 | 0.085 | 0.132 | 7.573 | 0.053 | 0.331 | 0.013 | 0.016 | 0.154 | 0.073 | 0.058 | 0.052 | 0.006 | 0.438 |
| Tsesnabank | 2012 | 0 | 0.105 | 0.07 | 0.078 | 0.118 | 8.504 | 0.018 | 0.132 | 0.01 | 0.009 | 0.12 | 0.081 | 0.048 | 0.045 | -1.014 | 0.538 |
| Alliance Bank | 2012 | 1 | 0.126 | 0.078 | 0.093 | 0.144 | 6.938 | 0.377 | 3.022 | 0.015 | 0.021 | 1.233 | 0.096 | 0.03 | -0.01 | 0.12 | 1.58 |
| ATF Bank | 2012 | 1 | 0.116 | 0.08 | 0.089 | 0.132 | 7.594 | 0.243 | 1.836 | 0.006 | -0.038 | -0.588 | 0.004 | 0.031 | 0.022 | -0.415 | 1.103 |
| BTA Bank | 2012 | 1 | 0.187 | 0.115 | 0.118 | 0.231 | 4.338 | 0.484 | 3.342 | 0.007 | -0.015 | 0.097 | 0.072 | -0.01 | -0.037 | -0.589 | 1.465 |
| Kazkommertsbank | 2012 | 1 | 0.162 | 0.131 | 0.123 | 0.193 | 5.169 | 0.145 | 0.827 | 0.004 | 0 | 0.003 | 0.055 | 0.055 | 0.025 | 0.255 | 0.636 |
| Nurbank | 2012 | 1 | 0.178 | 0.174 | 0.192 | 0.217 | 4.603 | 0.323 | 1.505 | 0.011 | -0.004 | -0.016 | 0.04 | 0.034 | 0.006 | -0.104 | 0.835 |
| Temirbank | 2012 | 1 | 0.114 | 0.078 | 0.095 | 0.129 | 7.764 | 0.471 | 3.586 | 0.015 | 0.002 | 0.008 | 0.068 | 0.039 | -0.005 | 0.329 | 2.439 |

Appendix 5B

Data for MDA. Logit and Probit Analyses (out sample)

| Banks | Year | Status | R1 | R2 | R3 | R4 | R5 | R6 | R7 | R8 | R9 | R10 | R11 | R12 | R13 | R14 | R15 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Bank Centercredit | 2013 | 0 | 0.129 | 0.086 | 0.091 | 0.149 | 6.735 | 0.098 | 0.607 | 0.009 | 0 | 0.005 | 0.048 | 0.019 | 0.011 | -0.669 | 0.623 |
| Bank RBK | 2013 | 0 | 0.172 | 0.166 | 0.173 | 0.208 | 4.82 | 0.024 | 0.102 | 0.016 | 0.003 | 0.018 | 0.092 | 0.066 | 0.061 | -0.228 | 0.711 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.123 | 0.084 | 0.102 | 0.141 | 7.102 | 0.149 | 0.789 | 0.008 | 0.025 | 0.192 | 0.065 | 0.041 | 0.03 | -0.018 | 0.744 |
| Kaspi Bank | 2013 | 0 | 0.147 | 0.079 | 0.084 | 0.173 | 5.788 | 0.065 | 0.365 | 0.018 | 0.032 | 0.283 | 0.125 | 0.082 | 0.057 | -0.892 | 1.641 |
| SB Sberbank | 2013 | 0 | 0.137 | 0.087 | 0.091 | 0.159 | 6.294 | 0.051 | 0.27 | 0.013 | 0.019 | 0.153 | 0.07 | 0.054 | 0.049 | 0.397 | 0.92 |
| Tsesnabank | 2013 | 0 | 0.114 | 0.064 | 0.067 | 0.128 | 7.806 | 0.022 | 0.148 | 0.012 | 0.017 | 0.213 | 0.09 | 0.059 | 0.056 | -0.962 | 0.485 |
| Alliance Bank | 2013 | 1 | 0.152 | 0.091 | 0.12 | 0.179 | 5.589 | 0.34 | 2.221 | 0.014 | 0.013 | 0.21 | 0.09 | 0.038 | 0.002 | -0.005 | 1.148 |
| ATF Bank | 2013 | 1 | 0.133 | 0.099 | 0.108 | 0.153 | 6.518 | 0.362 | 2.46 | 0.007 | -0.013 | -0.154 | 0.038 | 0.029 | 0.018 | -0.485 | 0.823 |
| BTA Bank | 2013 | 1 | 0.143 | 0.14 | 0.232 | 0.167 | 5.977 | 0.85 | 8.047 | 0.008 | -0.23 | -1.664 | -0.17 | -0.01 | -0.02 | -0.602 | 0.751 |
| Kazkommertsbank | 2013 | 1 | 0.153 | 0.126 | 0.122 | 0.18 | 5.543 | 0.179 | 1.102 | 0.005 | 0.001 | 0.003 | 0.047 | 0.062 | 0.032 | 0.225 | 0.503 |
| Nurbank | 2013 | 1 | 0.17 | 0.177 | 0.205 | 0.205 | 4.883 | 0.37 | 1.632 | 0.013 | -0.021 | -0.073 | 0.025 | 0.025 | 0.004 | -0.077 | 0.754 |
| Temirbank | 2013 | 1 | 0.122 | 0.07 | 0.084 | 0.139 | 7.176 | 0.446 | 3.071 | 0.017 | 0.05 | 0.204 | 0.109 | 0.057 | 0.016 | 0.241 | 1.418 |
| Bank Centercredit | 2014 | 0 | 0.132 | 0.085 | 0.092 | 0.152 | 6.568 | 0.163 | 1.709 | 0.008 | 0.002 | 0.013 | 0.046 | 0.05 | 0.037 | -0.328 | 0.456 |
| Bank RBK | 2014 | 0 | 0.096 | 0.066 | 0.087 | 0.106 | 9.455 | 0.031 | 0.276 | 0.015 | 0.007 | 0.075 | 0.093 | 0.057 | 0.052 | 0.265 | 0.851 |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0.153 | 0.095 | 0.112 | 0.18 | 5.548 | 0.163 | 0.776 | 0.008 | 0.035 | 0.228 | 0.056 | 0.058 | 0.044 | -0.041 | 0.734 |
| Kaspi Bank | 2014 | 0 | 0.12 | 0.059 | 0.073 | 0.136 | 7.34 | 0.122 | 1.041 | 0.02 | 0.038 | 0.319 | 0.114 | 0.087 | 0.064 | -0.232 | 2.266 |
| SB Sberbank | 2014 | 0 | 0.128 | 0.08 | 0.079 | 0.146 | 6.842 | 0.074 | 0.283 | 0.008 | 0.021 | 0.163 | 0.154 | 0.054 | 0.048 | -0.325 | 0.848 |
| Tsesnabank | 2014 | 0 | 0.101 | 0.061 | 0.066 | 0.113 | 8.875 | 0.037 | 0.342 | 0.01 | 0.018 | 0.175 | 0.082 | 0.055 | 0.051 | 0.075 | 0.731 |
| Alliance Bank | 2014 | 1 | 0.103 | 0.075 | 0.109 | 0.115 | 8.685 | 0.498 | 29.001 | 0.012 | 0.005 | 0.047 | 0.116 | 0.022 | -0.006 | 0.255 | 1.104 |
| ATF Bank | 2014 | 1 | 0.098 | 0.092 | 0.122 | 0.109 | 9.161 | 0.423 | 4.343 | 0.007 | 0 | 0.003 | 0.045 | 0.023 | 0.01 | 0.025 | 1.163 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| BTA Bank | 2014 | 1 | 0.156 | 0.141 | 0.25 | 0.185 | 5.394 | 0.849 | 8.513 | 0.007 | 0.018 | 0.114 | 0.079 | 0.057 | -0.02 | -0.197 | 1.448 |
| Kazkommertsbank | 2014 | 1 | 0.179 | 0.122 | 0.126 | 0.218 | 4.596 | 0.294 | 1.982 | 0.005 | 0.018 | 0.102 | 0.07 | 0.069 | 0.034 | -0.346 | 0.522 |
| Nurbank | 2014 | 1 | 0.173 | 0.151 | 0.184 | 0.209 | 4.787 | 0.293 | 1.327 | 0.013 | -0.131 | -0.759 | -0.079 | 0.027 | 0.006 | -0.296 | 1.017 |
| Temirbank | 2014 | 1 | 0.143 | 0.076 | 0.09 | 0.166 | 6.007 | 0.402 | 1.681 | 0.016 | 0.001 | 0.005 | 0.06 | 0.054 | 0.02 | -0.138 | 1.698 |

**Appendix 5C: Results of MDA Model on Out Sample Data from 1st January 2013 to 1st January 2014**

| Bank | Year | Assigned Status | Discriminant Scores | Predicted Status |
|---|---|---|---|---|
| Bank Centercredit | 2013 | 0 | -0.052 | 1** |
| Bank RBK | 2013 | 0 | 1.306 | 0 |
| Halyk Bank of Kazakhstan | 2013 | 0 | -0.490 | 1** |
| Kaspi Bank | 2013 | 0 | 2.354 | 0 |
| SB Sberbank | 2013 | 0 | -0.303 | 1** |
| Tsesnabank | 2013 | 0 | 2.208 | 0 |
| Alliance Bank | 2013 | 1 | -1.313 | 1 |
| ATF Bank | 2013 | 1 | -0.181 | 1 |
| BTA Bank | 2013 | 1 | -1.342 | 1 |
| Kazkommertsbank | 2013 | 1 | -0.940 | 1 |
| Nurbank | 2013 | 1 | -1.156 | 1 |
| Temirbank | 2013 | 1 | -1.100 | 1 |
| Bank Centercredit | 2014 | 0 | 0.290 | 0 |
| Bank RBK | 2014 | 0 | 0.106 | 0 |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0.063 | 0 |
| Kaspi Bank | 2014 | 0 | 1.574 | 0 |
| SB Sberbank | 2014 | 0 | 0.689 | 0 |
| Tsesnabank | 2014 | 0 | 0.200 | 0 |
| Alliance Bank | 2014 | 1 | -2.121 | 1 |
| ATF Bank | 2014 | 1 | -1.335 | 1 |
| BTA Bank | 2014 | 1 | -2.062 | 1 |
| Kazkommertsbank | 2014 | 1 | 0.096 | 0** |
| Nurbank | 2014 | 1 | -0.713 | 1 |
| Temirbank | 2014 | 1 | -0.352 | 1 |

** – Misclassified cases

**Source:** Author

**Appendix 5D: Results of Logit Model on Out Sample Data from 1st January 2013 to 1st January 2014**

| Bank | Date | Assigned Status | $Z_{lfs}$ | $p_{lfs}$ | Predicted Status |
|---|---|---|---|---|---|
| Bank Centercredit | 2013 | 0 | 0.189 | 0.547 | 1** |
| Bank RBK | 2013 | 0 | -2.546 | 0.073 | 0 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.622 | 0.651 | 1** |
| Kaspi Bank | 2013 | 0 | -4.075 | 0.017 | 0 |
| SB Sberbank | 2013 | 0 | 0.018 | 0.505 | 1** |
| Tsesnabank | 2013 | 0 | -3.730 | 0.023 | 0 |
| Alliance Bank | 2013 | 1 | 2.049 | 0.886 | 1 |
| ATF Bank | 2013 | 1 | 0.333 | 0.583 | 1 |
| BTA Bank | 2013 | 1 | 2.475 | 0.922 | 1 |
| Kazkommertsbank | 2013 | 1 | 1.317 | 0.789 | 1 |
| Nurbank | 2013 | 1 | 1.814 | 0.860 | 1 |
| Temirbank | 2013 | 1 | 1.508 | 0.819 | 1 |
| Bank Centercredit | 2014 | 0 | -0.607 | 0.353 | 0 |
| Bank RBK | 2014 | 0 | -0.657 | 0.341 | 0 |
| Halyk Bank of Kazakhstan | 2014 | 0 | -0.359 | 0.411 | 0 |
| Kaspi Bank | 2014 | 0 | -3.055 | 0.045 | 0 |
| SB Sberbank | 2014 | 0 | -1.325 | 0.210 | 0 |
| Tsesnabank | 2014 | 0 | -0.684 | 0.335 | 0 |
| Alliance Bank | 2014 | 1 | 3.370 | 0.967 | 1 |
| ATF Bank | 2014 | 1 | 2.123 | 0.893 | 1 |
| BTA Bank | 2014 | 1 | 3.552 | 0.972 | 1 |
| Kazkommertsbank | 2014 | 1 | -0.228 | 0.443 | 0** |
| Nurbank | 2014 | 1 | 1.140 | 0.758 | 1 |
| Temirbank | 2014 | 1 | 0.382 | 0.594 | 1 |

** – Misclassified cases

**Source:** Author

**Appendix 5E: Results of Probit Model on Out Sample Data from 1st January 2013 to 1st January 2014**

| Name | Date | Assigned Status | Zpa | $P_{pa}$ | Predicted Status |
|---|---|---|---|---|---|
| Bank Centercredit | 2013 | 0 | 0.275 | 0.608 | 1** |
| Bank RBK | 2013 | 0 | -2.294 | 0.011 | 0 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 0.322 | 0.626 | 1** |
| Kaspi Bank | 2013 | 0 | -3.438 | 0.000 | 0 |
| SB Sberbank | 2013 | 0 | -0.116 | 0.454 | 0 |
| Tsesnabank | 2013 | 0 | -3.460 | 0.000 | 0 |
| Alliance Bank | 2013 | 1 | 2.305 | 0.989 | 1 |
| ATF Bank | 2013 | 1 | 0.194 | 0.577 | 1 |
| BTA Bank | 2013 | 1 | 2.595 | 0.995 | 1 |
| Kazkommertsbank | 2013 | 1 | 0.709 | 0.761 | 1 |
| Nurbank | 2013 | 1 | 2.020 | 0.978 | 1 |
| Temirbank | 2013 | 1 | 1.820 | 0.966 | 1 |
| Bank Centercredit | 2014 | 0 | -0.815 | 0.207 | 0 |
| Bank RBK | 2014 | 0 | -0.640 | 0.261 | 0 |
| Halyk Bank of Kazakhstan | 2014 | 0 | -0.693 | 0.244 | 0 |
| Kaspi Bank | 2014 | 0 | -2.527 | 0.006 | 0 |
| SB Sberbank | 2014 | 0 | -1.587 | 0.056 | 0 |
| Tsesnabank | 2014 | 0 | -0.962 | 0.168 | 0 |
| Alliance Bank | 2014 | 1 | 3.438 | 1.000 | 1 |
| ATF Bank | 2014 | 1 | 1.817 | 0.965 | 1 |
| BTA Bank | 2014 | 1 | 3.451 | 1.000 | 1 |
| Kazkommertsbank | 2014 | 1 | -0.661 | 0.254 | 0** |
| Nurbank | 2014 | 1 | 1.378 | 0.916 | 1 |
| Temirbank | 2014 | 1 | 0.731 | 0.768 | 1 |

** – Misclassified cases

**Source:** Author

**Appendix 5F: Results of Integrated Bank Unsoundness Prediction Model on Out Sample Data from 1st January 2013 to 1st January 2014**

| Name | Date | Assigned Status | MDA | Logit | Probit | Integrated |
|---|---|---|---|---|---|---|
| Bank Centercredit | 2013 | 0 | 1 | 1 | 1 | 1** |
| Bank RBK | 2013 | 0 | 0 | 0 | 0 | 0 |
| Halyk Bank of Kazakhstan | 2013 | 0 | 1 | 1 | 1 | 1** |
| Kaspi Bank | 2013 | 0 | 0 | 0 | 0 | 0 |
| SB Sberbank | 2013 | 0 | 1 | 0 | 1 | 1** |
| Tsesnabank | 2013 | 0 | 0 | 0 | 0 | 0 |
| Alliance Bank | 2013 | 1 | 1 | 1 | 1 | 1 |
| ATF Bank | 2013 | 1 | 1 | 1 | 1 | 1 |
| BTA Bank | 2013 | 1 | 1 | 1 | 1 | 1 |
| Kazkommertsbank | 2013 | 1 | 1 | 1 | 1 | 1 |
| Nurbank | 2013 | 1 | 1 | 1 | 1 | 1 |
| Temirbank | 2013 | 1 | 1 | 1 | 1 | 1 |
| Bank Centercredit | 2014 | 0 | 0 | 0 | 0 | 0 |
| Bank RBK | 2014 | 0 | 0 | 0 | 0 | 0 |
| Halyk Bank of Kazakhstan | 2014 | 0 | 0 | 0 | 0 | 0 |
| Kaspi Bank | 2014 | 0 | 0 | 0 | 0 | 0 |
| SB Sberbank | 2014 | 0 | 0 | 0 | 0 | 0 |
| Tsesnabank | 2014 | 0 | 0 | 0 | 0 | 0 |
| Alliance Bank | 2014 | 1 | 1 | 1 | 1 | 1 |
| ATF Bank | 2014 | 1 | 1 | 1 | 1 | 1 |
| BTA Bank | 2014 | 1 | 1 | 1 | 1 | 1 |
| Kazkommertsbank | 2014 | 1 | 0 | 1 | 0 | 1 |
| Nurbank | 2014 | 1 | 1 | 1 | 1 | 1 |
| Temirbank | 2014 | 1 | 1 | 0 | 1 | 1 |

** – Misclassified cases

**Source:** Author