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# An assessment of the financial soundness of the Kazakh banks

Aigul P. Salina
*Satbayev University, Almaty, Kazakhstan, and*
Xin Zhang and Omaima A.G. Hassan
*Robert Gordon University, Aberdeen, UK*



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## Abstract

**Purpose** – The contribution of the banking industry to the financial crisis of 2007/8 has raised public concerns about the financial soundness of banks around the world with many countries still suffering the backlogs of this crisis. The continuous emergence of such crises at both national and international levels increases governments', bank regulators' and financial market participants' need for reliable tools to assess the financial soundness of banks. In this context, this study investigates the financial soundness of the Kazakh banking sector, which is ranked by the World Bank as the first in the world in terms of the percentage of nonperforming loans (NPL) to total gross loans in 2012.

**Design/methodology/approach** – Using data about all Kazakh banks over the period January 01, 2008 to January 01, 2014, the study identifies a number of accounting indicators that influence the financial soundness of banks using principal component analysis (PCA). Then, it uses the outcomes of the PCA in a cluster analysis and groups the Kazakh banks into sound, risky and unsound banks at two points in time: January 01, 2008 and January 01, 2014. This methodology was further tested against a ranking system of banks and proved to be more reliable in detecting risky banks.

**Findings** – Fifteen financial ratios were initially selected as accounting indicators for the assessment of bank financial soundness. Using PCA, twelve indicators were isolated, which explain five principal components of capital adequacy, return on assets, profitability, asset quality, liquidity and leverage. Then using the "*k*-means" method, the results suggest a structure of the Kazakh banking sector on January 01, 2008 that includes two groups of banks: sound and risky banks. On January 01, 2014, this structure of the banking system has changed to include three groups of banks: sound, risky and unsound banks. Thus, in 2014 a new group of banks has emerged, i.e. financially unsound banks.

**Practical implications** – The proposed cluster-based methodology has proven to be a reliable tool to detect the financial soundness of Kazakh banks, which makes us advocate its employability for bank monitoring and supervision purposes.

**Originality/value** – This study is the first to employ a cluster-based methodology to assess the financial soundness of a banking sector. This methodology can be used at a micro-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.

**Keywords** Financial soundness, Banks, Cluster analysis, Principal component analysis, Emerging economies, Eurasian

**Paper type** Research paper

## 1. Introduction

The financial soundness of a bank is a condition in which the financial indicators characterizing its capital adequacy, asset quality, liquidity and effectiveness are within certain limits to ensure the ability of a bank to survive negative market conditions (e.g. Čihák, 2007; Pukhov, 2013). Failing to achieve these limits will transfer a bank from a sound to an

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unsound status. The determination of these limits is the most important stage of the process of the assessment of financial soundness in the banking sector. These financial indicators vary continuously to reflect the influence of the political, economic, social and financial conditions of each country. Thus, the demarcation of financial soundness limits would better be developed for the banking sector of each country. While the literature on the financial soundness of banks (see Appendix 1–supplementary material) at the macro-level is rich (e.g. Gaganis *et al.*,2006; Ioannidis *et al.*, 2010; Fernández-Arias *et al.*, 2018), the number of micro-level studies has been recently growing (e.g. Rahman, 2017; Mittal and Mittal, 2017; Ouma and Kirori, 2019; Seyedi and Abdoli, 2019; Suresh *et al.*, 2019). Although cross-country studies could provide international benchmarks of the financial health of banks, it can mask crucial differences between local banks when there is a significant difference in the financial development of the different countries involved in the study. Thus, cross-country studies might fail to provide supervisory and regulatory bodies with relevant information to monitor the performance of local banks. In this context, the current study [1] examines the financial soundness of Kazakh banks using a combination of principal component analysis (PCA) and cluster analysis.

Kazakhstan provides an interesting case to study the financial soundness of banks as the level of nonperforming loans (NPL) has dramatically increased from 2.4% in 2007 to 36% in 2013, showing that the financial crisis of 2007/8 is still unfolding (IMF, 2014). In fact, the World Bank has ranked it first in the world according to the percentage of NPL to total gross loans in 2012 (Vorotilov, 2013). However, to date, there seems to be scarce international studies of the Kazakh banking sector.

This study contributes to the literature in several aspects. First, it contributes to the literature by proposing a simple, yet new, methodology to study the financial soundness of banks, i.e. a combination of PCA and cluster analysis. Second, it examines the financial soundness of banks in one of the most developed banking sectors in the Central Asian region and yet one of the leading countries worldwide in terms of the percentage of NPL to total gross loans. Third, it adds to the growing literature on the financial soundness of banks at micro-level by determining the structure of the banking system in a country and changes in this structure based solely on the performance of local banks. Using data on all Kazakh banks over the period from January 01, 2008 to January 01, 2014, the results suggest a structure of the Kazakh banking sector on January 01, 2008 that includes two groups of banks: sound and risky banks. This structure has changed on January 01, 2014 to include three groups of banks: sound, risky and unsound banks. Thus, in 2014, a new group of banks has emerged, i.e. financially unsound banks. On the one hand, these results highlight the dramatic deterioration of the financial health of Kazakh banks over the period January 01, 2008 to January 01, 2014. On the other hand, our results suggest that a combination of PCA and cluster analysis provides a simple and reliable tool to assess the financial soundness of a banking sector. This methodology can provide early warning signals to decision-makers and supervisory and regulatory bodies to detect vulnerable banks before they fail.

The rest of this paper is divided into seven sections: Section 2 provides an overview of the Kazakh banking sector. Section 3 briefly discusses related studies. Section 4 introduces a cluster-based methodology to assess the financial soundness of banks. Section 5 covers data analysis and discussion and section 6 checks the robustness of our results. Section 7 concludes the study.

## 2. The Kazakh banking sector

Kazakhstan is a post-Soviet emerging country which is transforming its economy from central planning to a free-market economy. The country is in the center of the Eurasian continent and is an active participant in international affairs. The country has transitioned from lower middle-income to upper middle-income status in the World Bank's classification of countries in less than two decades since its independence in 1991. Also, according to the World Bank's Doing Business report of 2019, Kazakhstan occupied the 28th place ahead of many developed countries such as Spain, France, Netherlands and Japan (World Bank Group, 2019).

The Kazakh financial sector is one of the most developed in the Central Asian region and occupies a leading position in the post-Soviet era. However, since 1991 the Kazakh banking sector has witnessed considerable consolidation with about 200 banks in 1993 falling to only 38 banks in 2014. At the end of 2007, the share of the banking sector assets to GDP in Kazakhstan amounted to 91%, which is comparable to that of Central and Eastern European countries. However, the global financial crisis of 2007/8 has dramatically undermined the Kazakh banking sector. For example, while the ratio of the banking sector assets to GDP has fallen from 91% in 2007 to 44% in 2013, the level of NPL of Kazakh banks has significantly increased from 2.7% in 2007 to 36% in 2013, which shows the extreme vulnerability of Kazakh banks. Since the financial crisis of 2007/8, 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 was growing but stabilized at 10% in 2018. Yet, the Kazakh banking sector has not recovered to pre-crisis levels despite the strong infusion of government capital into the equity of banks, debt restructuring and issuance of tougher standards. This, in turn, means that the Kazakh banking sector is still in urgent need for innovative approaches to detect the vulnerability of its banks to enable effective intervention in a timely manner.

## 3. Literature review

A review of the literature (see Appendix 1–supplementary material) shows that several prior studies on the financial soundness of banks are cross-country studies, which typically use macroeconomic variables and accounting-based indicators to assess the financial soundness of banks from different countries. For example, Gaganis *et al.* (2006); Ioannidis *et al.* (2010) and Fernández-Arias *et al.* (2018) develop quantitative models to classify banks from different countries into three groups based on their financial soundness to strong banks, adequate banks and banks with weaknesses and serious problems. On the other hand, micro-level studies focus on the financial soundness of banks within a particular country. This study is related to the latter strand of studies.

Micro-level studies can be classified into a number of streams. The first stream of studies focuses on measuring the financial soundness of banks using different models (e.g. Masud and Haq, 2016; Rahman, 2017; Dash, 2017; Mittal and Mittal, 2017; AlAli and Al-Yatama, 2019; Ouma and Kirori, 2019; Suresh *et al.*, 2019). The second stream of studies investigates changes in the financial soundness of banks overtime (e.g. Gasbarro *et al.*, 2002; Ginevičius and Podviezko, 2013). The third stream of studies tests the ability of different models in detecting the financial soundness of banks (e.g. Ashraf and Tariq, 2016). The fourth stream of studies investigates the determinants of the financial soundness of banks (e.g. Chang, 2016; Bae, 2019; Seyedi and Abdoli, 2019; Talibong and Simiyu, 2019). This study contributes to the first stream of studies by measuring the financial soundness of banks in a new setting, i.e. the Kazakh banks, and employing a novel methodology, i.e. a combination of PCA and cluster analysis. It also extends the micro-level literature on the financial soundness of banks by determining the structure of the banking system in a country and changes in that structure based solely on the performance of local banks.

This study also relates to, but differs from, the work of Gaganis *et al.* (2006); Ioannidis *et al.* (2010) and Fernández-Arias *et al.* (2018). Similar to these three studies, the current study classifies banks into three groups: sound, risky and unsound banks. However, this study differs in three important aspects. First, these three studies are cross-country studies, but the current study is conducted at a micro-level for the Kazakh banks only. Second, the current study uses a different methodology to those applied by those three studies, i.e. a combination of PCA and cluster analysis to assess the financial soundness of banks. Third, the models developed by Gaganis *et al.* (2006) needed preliminary assessment of banks and for that purpose they used bank credit ratings provided by Fitch. In contrast, our proposed cluster-based methodology does not require preliminary status or rating, rather it defines such status. Previous studies noted that cluster analysis also works on small samples with non-normally distributed data (Shuai *et al.*, 2013).

Finally, an assessment of financial soundness requires a set of variables that helps distinguish a group of banks with similar financial characteristics and identify the significant indicators to detect sound and unsound banks. Prior studies generally employ market-based measures and/or accounting-based measures. This study employs accounting-based measures to assess the financial soundness of Kazakh banks (e.g. Gasbarro et *al.,* 2002; Masud and Haq, 2016; Rahman, 2017; Ouma and Kirori, 2019). This is because the majority of these banks are not listed on a stock exchange. In addition, accounting-based measures have several advantages over market-based indicators (e.g. Agarwal and Taffer, 2008; Kliestik *et al.*, 2020). For example, bank default is the peak point of many years of negative performance which could be captured by accounting-based measures. Also, loan covenants rely on accounting rather than market information. Furthermore, the double-entry system ensures minimal effect of window dressing and changes in accounting policies.

## 4. Data and research methodology

This study utilizes a combination of PCA and cluster analysis to assess the financial soundness of the Kazakh banking sector. First, we identify the financial indicators that influence the financial soundness of banks using PCA. Second, we classify banks into sound, risky and unsound groups using cluster analysis. We use cluster analysis to determine groups of banks where a calibrated set of selected indicators behave in similar ways.

### *4.1 Data collection and indicators selection*

The research sample consists of the entire Kazakh banking sector, which includes 34 banks on the 1st of January 2008 and 37 banks on the 1st of January 2014 (see Appendix 2–supplementary material). The former date represents the pre-crisis period. Data is collected from the annual financial reports of banks and reports of the National Bank of Kazakhstan. The entire dataset of 256 bank-year observations is used to run the PCA, but cluster analysis is employed cross-sectionally at two points in time: January 01, 2008 and January 01, 2014. SPSS software version 21 was used to perform the analysis.

A set of 15 financial indicators are selected for the current study based on a review of relevant prior studies (see Appendix 3–supplementary material). These indicators reflect the main characteristics of capital adequacy, asset quality, management, earnings and liquidity as shown in Appendix 3. In addition, some of these ratios are borrowed from the IMF's financial soundness indicators (*R*1, *R*2, *R*3, *R*6, *R*7, *R*9, *R*10 and *R*15) and prudential norms of Kazakh banks (*R*1, *R*2, *R*3, *R*5, *R*6, *R*7, *R*10, *R*12, *R*13 and *R*15).

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 ability of the management to identify, properly assess, mitigate and control these risks in a timely manner. Five ratios are used for this category, namely: capital adequacy ratio, regulatory capital to risk-weighted assets, regulatory Tier 1 capital to risk-weighted assets, equity to debt ratio and financial leverage ratio.

Asset quality reflects the amount of existing and potential credit default risks inherent in credit loan, investment portfolios, fixed assets, other assets and other off-balance sheet transactions. Two ratios are used for this category, namely: NPL to total gross loans and NPL net of provisions to capital.

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. We use the ratio of gross wages and salaries to assets as a proxy for management quality.

Earnings reflect the ability of the management to create revenues and reduce costs such as extraordinary costs, loan losses and legal costs. Five profitability indicators are selected, namely: return on assets, return on equity, earnings before interest and taxation (EBIT) to total assets, net interest margin and interest rate spread.

Finally, banks are required to maintain sufficient liquidity to meet their cash obligations and the needs of their clients. Two ratios are selected, namely: working capital to total assets ratio and current ratio.

### *4.2 Cluster methodology*

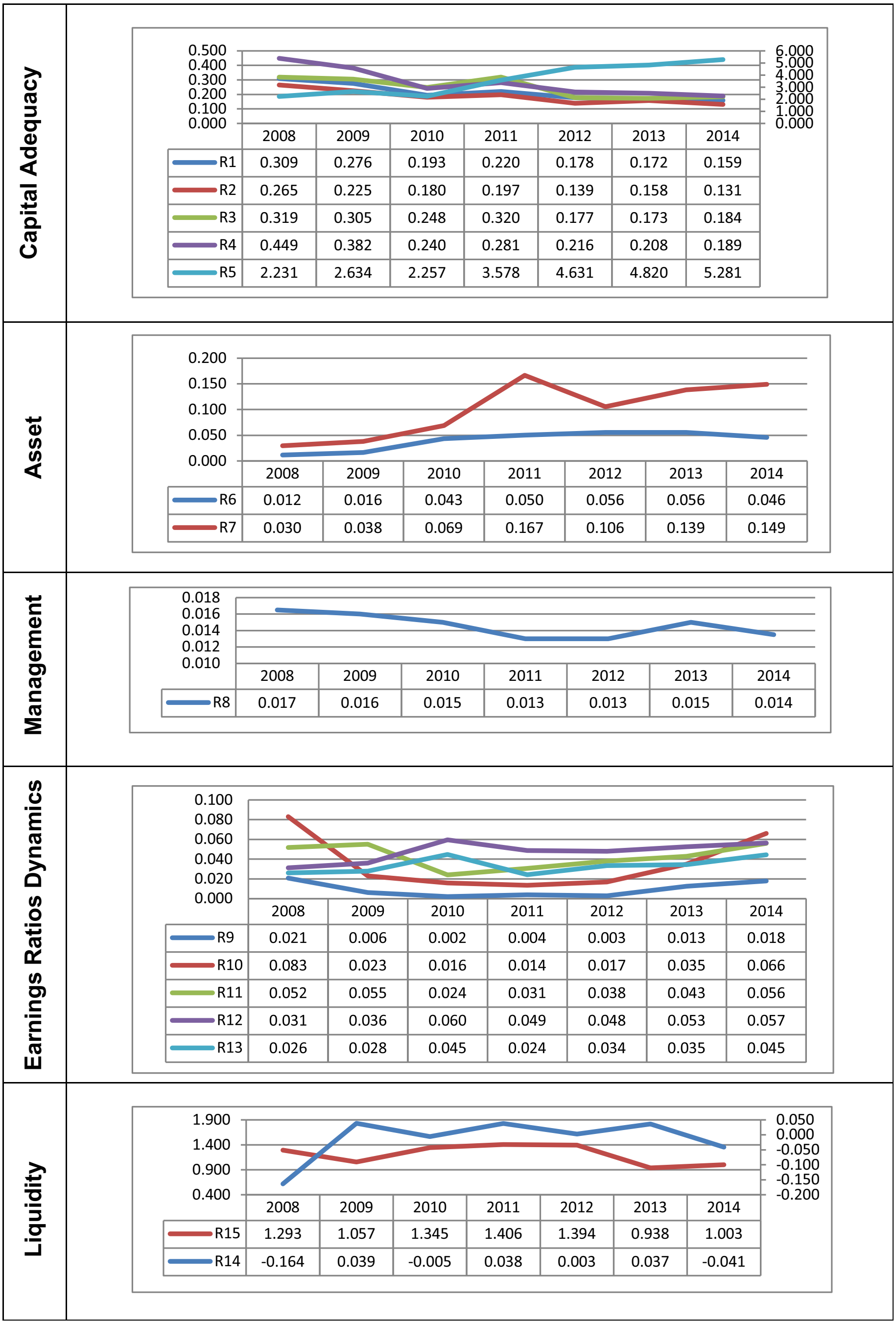
Many studies have used cluster methodology in Finance in general and in Banking, in particular (see Appendix 4–supplementary material). A cluster methodology is typically used in combination with a data mining approach such as factor analysis or PCA (e.g. Safdari *et al.*, 2005; Dao and Khanh, 2014; Cyree *et al.*, 2020). For e.g. Safdari *et al.* (2005) use PCA and cluster analysis to allocate 17 Armenian banks into similar groups, based on 13 accounting-based indicators. Cluster analysis searches for a “natural” split in the data and puts it in distinct groups that are remote from each other (Henning, 2015). It is usually used when data are presented as matrices of proximity, or the distances between objects or data points are in a multidimensional space. It focuses on identifying 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. Almost all studies in Appendix 4 use cluster analysis to produce final results such as a recognition of vulnerable banks or an identification of potentially failing banks. Division of banks into groups is usually made to specify their position in peer groups and the calculation of peer group ratio average.

This study applies a novel methodology to identify the financial soundness of banks, i.e. a combination of PCA and cluster analysis, which, to the best of our knowledge, was not employed in this context before. This methodology can be used to monitor changes in the structure of a banking sector and detect early warning signals for the deterioration of the financial health of banks.

## 5. Data analysis and discussion

### *5.1 Demarcation of financial soundness limits*

This section presents the descriptive statistics of the selected variables for the Kazakh banking sector in Figure 1 followed by a demarcation of the different ratios based on the median value of each variable over the period from January 01, 2008 to January 01, 2014. The results of this step provide the limits which divide the Kazakh banks into sound, risky and unsound banks. It is necessary to note that these limits serve as flags rather than standards in the process of identifying clusters.




**Capital Adequacy**

| | 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 |

**Asset**

| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|
| R6 | 0.012 | 0.016 | 0.043 | 0.050 | 0.056 | 0.056 | 0.046 |
| R7 | 0.030 | 0.038 | 0.069 | 0.167 | 0.106 | 0.139 | 0.149 |

**Management**

| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|
| R8 | 0.017 | 0.016 | 0.015 | 0.013 | 0.013 | 0.015 | 0.014 |

**Earnings Ratios Dynamics**

| | 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 |

**Liquidity**

| | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 |
|---|---|---|---|---|---|---|---|
| R15 | 1.293 | 1.057 | 1.345 | 1.406 | 1.394 | 0.938 | 1.003 |
| R14 | -0.164 | 0.039 | -0.005 | 0.038 | 0.003 | 0.037 | -0.041 |

**Figure 1.**
Demarcation of financial soundness limits (01.01.2008–01.01.2014)

Figure 1 shows that the first four capital adequacy ratios have the same downtrend during the analyzed period, while the curve of the debt to equity ratio (*R*5) clearly characterizes the deterioration in the banks' equity. It has increased steadily from 2.231 in 2008 to 5.281 in 2014.

In addition, Figure 1 also shows that the NPL to total gross loans ratio (*R*6) and the NPL net of provisions to capital ratio (*R*7) were steadily growing from 2008 to 2014. During this period, *R*6 increased four times, and *R*7 increased five times to confirm the deterioration in asset quality of Kazakh banks. This is hardly surprising since the World Bank ranked Kazakhstan the first in the world for the volume of NPL in 2012 (Vorotilov, 2013). The authorities introduced various approaches to control NPL in 2011, but in 2014 the ratio of NPL has further increased to 36% compared to 2.7% in 2007. IMF (2014) noted the slow progress in resolving NPLs in Kazakhstan and marked the country as the world "leader" in NPL. Figure 1 also shows the fluctuation in the salaries to total assets ratio (*R*8) which decreased from 0.017 in 2008 to 0.013 in 2011.

In addition, return on assets (*R*9) and return on equity (*R*10) had the highest values in 2008. They decreased sharply in 2010 and 2011 and returned close to pre-crisis levels in 2014. The deterioration of EBIT to assets (*R*11) started from 2009, and in 2014 the indicator reached pre-crisis level. The lowest values of the net interest rate margin (*R*12) at 0.031 is observed in 2008 and the interest rate spread (*R*13) at 0.024 in 2011. The peak values for these two indicators were in 2010 at 0.060 and 0.045 respectively. The values of these indicators in 2011 roughly correspond to those of 2008, and since 2011 they have gradually increased reaching 0.057 and 0.045 in 2014 respectively.

Figure 1 also shows that the value of the current liquidity ratio (*R*15) was 1.293 in 2008 and then it reached a peak of 1.394 in 2012 and declined to 1.004 in 2014. The working capital to total assets (*R*14) was negative in 2008, 2010 and 2014.

Calculated limits are relative to their context. However, the approach is useful for grouping banks by the degree of financial soundness in situations where bank credit ratings are not reliable or available. For example, in Kazakhstan during the last fifteen years, only 12–26 banks out of 38 had ratings assigned by Standard and Poor's, Fitch or Moody's according to the Kazakh Stock Exchange.

Following the Global Financial Stability Report (IMF, 2012), quartiles are used in this study to set the limits of financial soundness, and banks were classified into three groups: the worst quartile for unsound banks, the next-to-worst quartile for risky banks and the remaining two quartiles for sound banks. This study uses the median because the data is not normally distributed. So, in this case, the two quartiles above the median reveal sound banks, and the lower two reveal risky and unsound banks as can be seen from Table 1. These limits will be used for Step 4 of the cluster-based methodology of the assessment of financial soundness to determine the structure of the banking sector.

### *5.2 Principal component analysis*

PCA is used to analyze annual data for the period from January 01, 2008 to January 01, 2014 for all commercial Kazakh banks with 256 bank-year observations. The process includes the analysis of the pairwise correlations between the variables, the extraction of the principal components, the rotation of the principal components to simplify the structure and the interpretation of the principal components.

Based on the results obtained from the PCA, three variables (*R*8, *R*10 and *R*14) were excluded from the set of 15 variables. The remaining twelve indicators explain five principal components of capital adequacy, return on assets, profitability, asset quality, liquidity and leverage as can be seen in detail below.

*5.2.1 Correlation matrix, KMO and Bartlett tests.* To perform PCA, a Spearman's correlation matrix (see Appendix 5–supplementary material) was created to present the

| Selected variables | | 1st limit "unsound banks" | 2nd limit "risky banks" | 3rd limit "sound banks" |
|---|---|---|---|---|
| Capital adequacy ratio (CAR) | *R*1 | <0.143 | 0.143–0.214 | >0.214 |
| Regulatory capital to risk-weighted assets ratio | *R*2 | <0.098 | 0.098–0.197 | >0.197 |
| Regulatory Tier 1 capital to risk-weighted assets ratio | *R*3 | <0.130 | 0.130–0.235 | >0.235 |
| Equity to debt ratio | *R*4 | <0.164 | 0.164–0.278 | >0.278 |
| Financial leverage | *R*5 | >5.923 | 3.929–5.923 | <3.929 |
| Nonperforming loans to total gross loans | *R*6 | >0.065 | 0.036–0.065 | <0.036 |
| Nonperforming loans net of provisions to capital | *R*7 | >0.381 | 0.076–0.381 | <0.076 |
| Salary to total assets | *R*8 | <0.010 | 0.010–0.015 | >0.015 |
| Return on assets | *R*9 | <0.004 | 0.004–0.009 | >0.009 |
| Return on equity | *R*10 | <0.011 | 0.011–0.027 | >0.027 |
| EBIT to total assets | *R*11 | <0.032 | 0.032–0.049 | >0.049 |
| Net interest rate margin | *R*12 | <0.035 | 0.035–0.050 | >0.050 |
| Interest rate spread | *R*13 | <0.022 | 0.022–0.038 | >0.038 |
| Working capital to total assets | *R*14 | <−0.099 | −0.099–0.040 | >0.040 |
| Current ratio | *R*15 | <0.884 | 0.884–1.114 | >1.114 |

**Table 1.**
Limits of financial soundness

correlations between the variables. It shows that the correlation coefficients are within acceptable level. Also, Kaiser-Meyer-Olkin (KMO) and Bartlett's test (Appendix 6–supplementary material) are performed to check if a PCA is appropriate. The value of 0.635 in KMO test indicates satisfactory adequacy of the sample. The results for the Bartlett's test of sphericity, which is the criterion for the degree of correlation of variables, show that that the data is acceptable to run the PCA.

*5.2.2 Extraction of principal components.* The extraction of principal components is the next stage of the PCA through the analysis of the vector of eigenvalues of the principal components listed (see Appendix 7–supplementary material). According to Kaiser's criterion, the first five principal components should be retained as their eigenvalues exceed the threshold level of 1 (Nasledov, 2013). These five principal components explain 70.259% of the variance in the financial ratios.

*5.2.3 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 structure that simplifies the interpretation of the components by minimizing the number of variables with high loading on each component. The rotation of components does not affect the mathematical rigor of the analysis, i.e. 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 (see Appendix 8–supplementary material).

Appendix 8 shows that the indicators *R*8, *R*10 and *R*14 are not efficient in explaining the selected five components. Therefore, they must be excluded from the analysis. Rerunning the PCA on these twelve indicators show that the first five principal components are capable of explaining 83% of the variation in these variables.

*5.2.4 Interpretation of principal components.* The following conclusions can be drawn from the analysis of component loading matrices (Satina, 2008):

(1) The first component is closely related to four indicators, namely: the capital to assets ratio (*R*1), the regulatory capital to risk-weighted assets ratio (*R*2), the regulatory Tier 1 capital to risk-weighted assets ratio (*R*3) and the debt to equity ratio (*R*5). The four original attributes explain 97.3% of the variance of the first component.

(2) The second component can be titled the return on assets as it is closely related to the ratio of the return on assets (*R*9) and the ratio of EBIT to total assets (*R*11). These indicators explain 83.8% of the variance of the second component.

(3) The third component is explained by the net interest margin (*R*12) and the interest rate spread (*R*13). These two attributes explain 94.6% of the variance of the second component.

(4) The fourth component is closely related to the ratio of NPL net of provisions to capital (*R*7) and the ratio of NPL net of provisions to total loans (*R*6). The two original attributes explain 96.4% of the variance of the fourth component.

(5) The fifth component is closely related to the ratio of total equity to debt (*R*4) and the current liquidity ratio (*R*15). These two indicators explain 95.3% of the variance of the fifth component.

### *5.3 Cluster analysis*

In the previous step, five components described by twelve indicators are produced using PCA. The next step is to conduct a cluster analysis using the five principal components which characterize the financial soundness of banks. Cluster analysis, in this context, classifies banks into mutually exclusive groups according to the extent of their financial soundness.

This study employs the "*k*-means" method to identify the distance between groups (results are not tabulated). It is applied cross-sectionally at two points in time: January 01, 2008 and January 01, 2014. These dates are deliberately chosen to explore the evolution of clusters over time. The analysis is performed on all 34 Kazakh banks representing the entire banking system on the 1st of January 2008 and 37 banks on the 1st of January 2014. In total, five banks are identified as outliers and removed from the analysis, namely: Master Bank and TPBK in 2008 and Alliance Bank, BTA Bank, Home Credit Bank in 2014. Then the medians of indicators of the different clusters of banks are identified and presented in Table 2.

The median values of the financial ratios calculated for each cluster correspond to the limits of financial soundness. Interpretation of cluster results is usually carried out using

| Year | Cluster | Number of banks | Component 1 | | | | Component 2 | | Component 3 | | Component 4 | | Component 5 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | R1 | R2 | R3 | R5 | R9 | R11 | R12 | R13 | R6 | R7 | R15 | R4 |
| 22008 | 1 | 10 | 00.666 | 00.636 | 00.806 | 00.503 | 00.022 | 00.048 | 00.051 | 00.035 | 00.000 | 00.000 | 11.381 | 22.023 |
| | 2 | 7 | 00.329 | 00.278 | 00.330 | 22.035 | 00.023 | 00.052 | 00.036 | 00.031 | 00.013 | 00.025 | 00.744 | 00.491 |
| | 3 | 15 | 00.154 | 00.095 | 00.142 | 55.719 | 00.017 | 00.053 | 00.025 | 00.022 | 00.015 | 00.063 | 11.350 | 00.175 |
| 22014 | 1 | 8 | 00.657 | 00.619 | 00.866 | 00.524 | 00.018 | 00.023 | 00.061 | 00.050 | 00.045 | 00.048 | 22.054 | 11.920 |
| | 2 | 22 | 00.145 | 00.110 | 00.147 | 55.943 | 00.019 | 00.063 | 00.056 | 00.048 | 00.034 | 00.174 | 00.850 | 00.169 |
| | 3 | 4 | 00.158 | 00.107 | 00.124 | 55.397 | 00.001 | 00.053 | 00.041 | 00.015 | 00.348 | 11.832 | 11.090 | 00.188 |

**Table 2.**
Median values distributed by limits of financial soundness and color predominance

financial ratios even if cluster analysis is performed on the principal components or factors (e.g. Dao and Khanh, 2014; Şchiopu, 2010; Satina, 2008). Financial ratios reflect the distinctive features and characteristics of each cluster. They help summarize the common characteristics of the obtained clusters. Table 2 shows the median values of the financial soundness indicators of the different clusters and their corresponding colors based on a color code. Each cell has a definite color. While a red color indicates a value in the 1st quartile of "Unsound Banks", a yellow color shows values of the 2nd quartile "Risky Banks" and a green color shows the rest as "Sound Banks". The further distribution of clusters into groups is performed according to the principle of color predominance. This principle emphasizes the special status of the red color when putting banks into groups or clusters, where the presence of the red color in a cluster for more than 20% decreases it one level of financial soundness. The 20% threshold is defined following the Pareto principle which is also known as the 80/20 rule. This principle means that roughly 80% of the effects comes from 20% of the causes (Newman, 2005). 20% of 12 indicators is 2.4, thus if more than 2 indicators are marked red, the financial soundness degree of the group decreases one level.

In 2008, clusters 1 and 2 are grouped into sound banks as there are no more than 2 red ratios in both clusters, while cluster 3 is downgraded to risky banks due to the existence of 3 ratios in red category. In 2014, cluster 1 is mainly in green with only 1 red ratio, so this cluster forms the group of sound banks, while cluster 2 is downgraded to risky group with two red ratios, and cluster 3 was further downgraded to unsound group due to the existence of more than two red ratios.

Table 3 shows the different clusters of financial soundness by the median values of the financial indicators at two points in time: January 01, 2008 and January 01, 2014. Two groups of banks are formed on January 01, 2008: sound and risky banks, while three groups of banks are formed on January 01, 2014: sound, risky and unsound banks. *The first group of sound banks* on the 1st of 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 an adequate return on assets. *The second group of risky banks* shows a low level of capital adequacy, a low net interest rate margin and interest rate spread, an adequate asset quality and a medium profitability.

*The first group of sound banks* on the 1st of 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 an adequate level of return on assets.

| Groups of financial soundness | | Sound banks | | Risky banks | | Financially unsound banks | |
|---|---|---|---|---|---|---|---|
| Year | | 2008 | 2014 | 2008 | 2014 | 2008 | 2014 |
| Number of banks | | 19 | 9 | 15 | 22 | NA | 6 |
| Capital to assets ratio | *R*1 | 0.614 | 00.641 | 00.154 | 0.145 | NA | 0.150 |
| Regulatory capital to risk-weighted assets | *R*2 | 0.416 | 00.617 | 00.095 | 0.110 | NA | 0.107 |
| Regulatory Tier 1 capital to risk-weighted assets | *R*3 | 0.722 | 00.835 | 00.142 | 0.147 | NA | 0.124 |
| Equity to debt | *R*4 | 1.500 | 11.789 | 00.175 | 0.169 | NA | 0.176 |
| Financial leverage | *R*5 | 0.667 | 00.559 | 55.719 | 5.943 | NA | 5.701 |
| NPL to total gross loans | *R*6 | 0.005 | 00.035 | 00.015 | 0.034 | N/A | 0.413 |
| NPL to capital | *R*7 | 0.009 | 00.057 | 00.063 | 0.174 | NA | 3.163 |
| Return on assets | *R*9 | 0.022 | 00.023 | 00.017 | 0.019 | NA | 0.003 |
| Earnings before interest and taxes to assets | *R*11 | 0.050 | 00.023 | 00.053 | 0.063 | NA | 0.065 |
| Net interest margin | *R*12 | 0.036 | 00.064 | 00.025 | 0.056 | NA | 0.041 |
| Interest rate spread | *R*13 | 0.031 | 00.050 | 00.022 | 0.048 | NA | 0.008 |
| Current liquidity ratio | *R*15 | 1.120 | 22.588 | 11.350 | 0.850 | NA | 1.134 |

**Table 3.**
A comparison of the median values of financial soundness of the different clusters of banks

*The second group of risky banks* shows a low level of capital adequacy, high net interest rate margin and interest rate spread, low quality of assets and high EBIT to assets. *The third group of unsound banks* shows a low level of capital adequacy, a low net interest rate margin and interest rate spread and the lowest asset quality, return on assets and regulatory Tier 1 capital to risk-weighted assets ratio. It is worth noting that there has been a marked deterioration in the quality of assets in January 2014, where the ratios of NPLs to total gross loans and to capital have increased significantly for all the selected clusters, which led to the emergence of a new group of financially unsound banks.

Table 4 shows Kazakh banks at two points in time: 2008 and 2014 and the migrations of banks between the distinct levels of financial soundness. It demonstrates the deterioration in

| 2008 | | | | 2014 | | | |
|---|---|---|---|---|---|---|---|
| **No.** | **Bank*** | **Assets (million Tenge )** | **%** | **No.** | **Bank*** | **Assets (million Tenge)** | **%** |
| 1 | SB Taib Kazakh Bank | 2,031 | 0.02% | 1 | SB Taib Kazakh Bank | 21,297 | 0.14% |
| 2 | MB Alma-Ata (Home Credit Bank) ** | 4,109 | 0.04% | 2 | Home Credit Bank ** | 117,412 | 0.78% |
| 3 | Danabank (SB PNB Kazakhstan)** | 6, 205 | 0.05% | 3 | SB PNB Kazakhstan** | 13,815 | 0.09% |
| 4 | SB KZI bank | 9,010 | 0.08% | 4 | SB KZI bank | 26,104 | 0.17% |
| 5 | Zaman-Bank | 1,585 | 0.01% | 5 | Zaman-Bank | 14,559 | 0.10% |
| 6 | SB NB of Pakistan in Kazakhstan | 1,386 | 0.01% | 6 | SB NB of Pakistan in Kazakhstan | 5,560 | 0.04% |
| 7 | Demir Kazakhstan Bank (Bank Positive Kazakhstan) ** | 14,652 | 0.13% | 7 | Bank Positive Kazakhstan ** | 21,375 | 0.14% |
| 8 | Express Bank (dissolved) | 2,344 | 0.02% | 8 | Al Hilal Islamic Bank (new) | 17,042 | 0.11% |
| 9 | Masterbank (dissolved) | 2,021 | 0.02% | 9 | Shinhan Bank Kazakhstan (new) | 17,482 | 0.12% |
| 10 | SB Sberbank of Russia | 61,697 | 0.53% | 1 | SB Sberbank of Russia | 1,035,823 | 6.86% |
| 11 | Kazinkombank (Bank RBK)** | 1,728 | 0.01% | 2 | Bank RBK** | 222,775 | 1.47% |
| 12 | SB Lariba-Bank (AsiaCredit Bank)** | 6,404 | 0.05% | 3 | AsiaCredit Bank** | 92,262 | 0.61% |
| 13 | Delta Bank | 19,991 | 0.17% | 4 | Delta Bank | 190,266 | 1.26% |
| 14 | Metrokombank (ForteBank)** | 2,835 | 0.02% | 5 | ForteBank** | 38,309 | 0.25% |
| 15 | SB Alfa-Bank | 25,365 | 0.22% | 6 | SB Alfa-Bank | 171,024 | 1.13% |
| 16 | Senim-Bank (Qazaq Banki)** | 2,500 | 0.02% | 7 | Qazaq Banki** | 48,647 | 0.32% |
| 17 | SB Bank of China in Kazakhstan | 7,250 | 0.06% | 8 | SB Bank of China in Kazakhstan | 104,705 | 0.69% |
| 18 | Eximbank Kazakhstan | 38,567 | 0.33% | 9 | Eximbank Kazakhstan | 55,097 | 0.36% |
| 19 | TPBK | 5,570 | 0.05% | 10 | TPBK | 49,467 | 0.33% |
| | | | | 11 | Bank Astana-Finance (new) | 79,552 | 0.53% |
| 1 | Citibank Kazakhstan | 81,856 | 0.70% | 12 | Citibank Kazakhstan | 324,765 | 2.15% |
| 2 | SB HSBC Bank of Kazakhstan | 72,496 | 0.62% | 13 | SB HSBC Bank of Kazakhstan | 187,463 | 1.24% |
| 3 | Bank Caspian (Kaspi Bank) ** | 257,423 | 2.21% | 14 | Kaspi Bank ** | 850,886 | 5.63% |
| 4 | Tsesnabank | 150,039 | 1.29% | 15 | Tsesnabank | 923,679 | 6.11% |
| 5 | Bank CenterCredit | 880,898 | 7.56% | 16 | Bank CenterCredit | 1,072,420 | 7.10% |
| 6 | SB ABN Amro Bank Bank (SB RBS Kazakhstan) ** | 120,568 | 1.03% | 17 | SB RBS Kazakhstan** | 51,949 | 0.34% |
| 7 | Eurasian Bank | 183,797 | 1.58% | 18 | Eurasian Bank | 587,432 | 3.89% |
| 8 | Kazinvestbank | 57,936 | 0.50% | 19 | Kazinvestbank | 92,846 | 0.61% |
| 9 | Halyk Bank of Kazakhstan | 1,567,245 | 13.45% | 20 | Halyk Bank of Kazakhstan | 2,441,764 | 16.16% |
| | | | | 21 | Bank Kassa Nova (new) | 56,214 | 0.37% |
| | | | | 22 | SB VTB Bank Kazakhstan (new) | 143,964 | 0.95% |
| 10 | Kazkommertsbank | 2,714,259 | 23.29% | 1 | Kazkommertsbank | 2,500,987 | 16.56% |
| 11 | Nurbank | 204,040 | 1.75% | 2 | Nurbank | 252,802 | 1.67% |
| 12 | Alliance Bank | 1,192,070 | 10.23% | 3 | Alliance Bank | 562,026 | 3.72% |
| 13 | Bank Turanalem (BTA Bank) ** | 2,648,603 | 22.72% | 4 | BTA Bank ** | 1,516,956 | 10.04% |
| 14 | ATF Bank | 989,598 | 8.49% | 5 | ATF Bank | 895,248 | 5.93% |
| 15 | Temirbank | 325,928 | 2.80% | 6 | Temirbank | 302,608 | 2.00% |

**Note(s):** *Sound groups are coloured in green, Risky in yellow and unsound group in red. **Bank has been renamed

**Table 4.**
Clusters of banks on January 01, 2008 and January 01, 2014

the financial health of the Kazakh banking sector in terms of the size of bank assets of each group to the total assets of the banking sector. Although the number of sound banks has dropped from 19 in 2008 to nine in 2014, this group preserves its asset weighting in the sector (1.27% in 2008 vs. 1.69% in 2014). Meanwhile, the proportion of the assets of risky banks has dropped from 98.73% in 2008 to 58.39% in 2014. This is due to the emergence of the group of unsound banks (six banks) in 2014, which covers 39.93% of the total assets of the Kazakh banking sector.

## 6. Robustness test

As a robustness check of our methodology, we compare the results of the cluster-based methodology with a ranking system proposed by Al-Osaimy and Bamakhramah (2004) and Othman (2013). This system ranks banks based on their financial performance using a 10-point scale; where one indicates the worst, while ten presents the best. Ranks are assigned to each of the twelve financial ratios, then an overall average rank for each bank is calculated at two points in time: January 01, 2008 and January 01, 2014. For $R1$, $R2$, $R3$, $R4$, $R9$, $R11$, $R12$, $R13$ and $R15$ ratios, the best value is the highest value and the worst is the smallest. Whereas, for $R5$, $R6$ and $R7$ ratios, the best value is the smallest and the worst value is the largest.

A comparison of the results of a bank's rank (using the average ranking score) to its corresponding cluster (using the color code), see Appendix 9–supplementary material, shows that the results of the cluster-based methodology almost coincides with the results of bank ranking. Exceptions are: The Alliance Bank and Kazinvestbank. In this case, cluster analysis caught the deteriorating trend in the financial performance of Alliance Bank, which defaulted in April 2009. Also, the cluster-based methodology has more reliably captured the tendency of the deteriorating financial health of Kazkommertsbank. This bank received financial assistance from the government in 2016 and was sold to Halyk Bank for $1 in 2017.

In addition, we rerun the cluster analysis for 2013 (see Appendix 9–supplementary material). The results are generally consistent with those for 2014, apart from three banks migrating to a lower group in 2014. These include TPBK and Qazaq Banki moving from sound group to the risky banks and Kazkommertsbank migrating to unsound group.

## 7. Concluding remarks

This study contributes to the literature by investigating the financial soundness of the Kazakh banking sector using a combination of PCA and cluster analysis. The results suggest a structure of the Kazakh banking sector on January 01, 2008 that includes two groups of banks: sound and risky banks. On January 01, 2014, this structure of the banking system has changed to include three groups of banks: *sound, risky and unsound banks.* Thus, in 2014 a new group of banks has emerged, i.e. financially unsound banks. This methodology was further tested against a ranking system of banks and proved to be more reliable in detecting risky banks.

Our results highlight the dramatic deterioration of the financial health of the banking sector which has impacted its structure. On January 01, 2008 there were no unsound banks in Kazakhstan. The number of risky banks accounted for 44% of the total number of banks in the database and sound banks accounted for 56%. On January 01, 2014 there were 16% unsound banks, 60% risky banks and 24% sound banks. The depth of the financial fragility of Kazakh banks is further pronounced by the fact that two of the six financially unsound banks are among the top five largest banks in Kazakhstan. The total assets of the financially unsound banks accounts for 40% of the total assets of the entire Kazakh banking system.

The findings of this study are of interest to bank regulators and supervisory bodies who 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 the banking sector is not sufficiently mature. Our proposed cluster-based methodology provides a simple, yet reliable, tool to predict the financial health of banks and help monitor changes in their status regularly. Although it is beyond the remit of the current study to recommend possible remedies to the central bank, the set of financial ratios used in the PCA can help identify areas that need attention from the management of banks and potentially from the supervisory bodies.

The proposed cluster-based methodology has proven to be a reliable tool to detect the financial soundness of Kazakh banks, which makes us advocate its employability for bank monitoring and supervision. However, the methodology is inevitably suggestive. According to Sclove (2001) and Marsh *et al.* (2003) there is no right or wrong cluster analysis solution but only different viewpoints of the same set of data. Future studies can further examine the reliability of this methodology using data from different countries where credit ratings can provide some benchmarks. In addition, this paper employs PCA using panel data analysis and cluster analysis using cross-sectional analysis at two points in time, i.e. 2008 and 2014, due to data availability. If more data is to be available in the future, scholars might replicate the analysis to see if these results continue to hold.

## Note

1. This paper is based on the principal author's unpublished PhD thesis.

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## Further reading

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## Appendix

Appendixes of this article are included in a supplementary document which is available at: https://rgu-repository.worktribe.com/output/906761

## Corresponding author

Omaima A.G. Hassan can be contacted at: o.hassan@rgu.ac.uk

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