

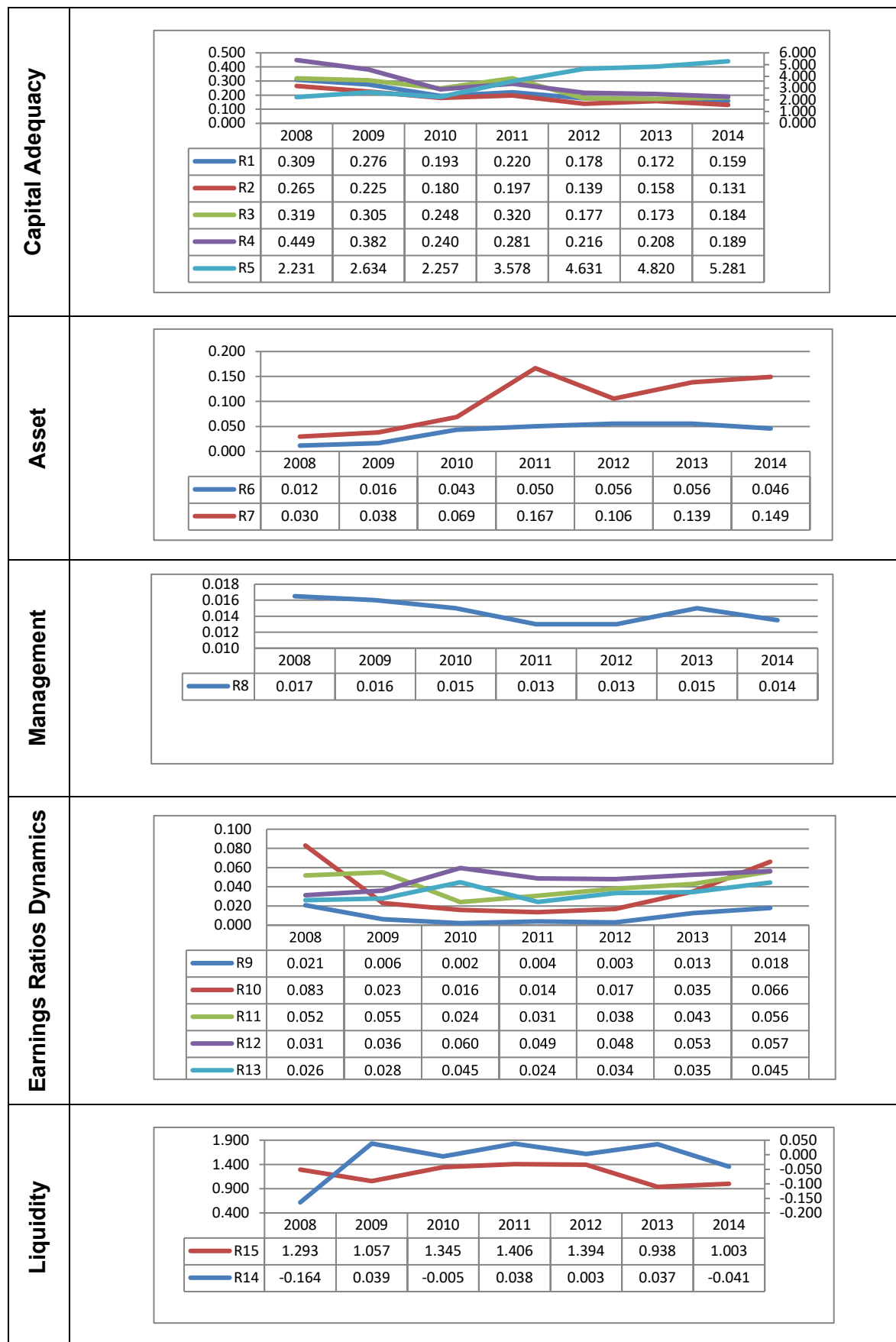
# An assessment of the financial soundness of the Kazakh banks. [Tables and Appendices]

SALINA, A.P., ZHANG, X. and HASSAN, O.A.G.

2021

©2021 Salina, A.P., Zhang, X. and Hassan, O.A.G.

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



**Table 1: Limits of Financial Soundness**

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
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
EBIT to total 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

**Table 2: Median Values Distributed by Limits of Financial Soundness and Colour predominance**

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 3: A Comparison of the Median Values of Financial Soundness of the different clusters of banks**

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	R1	0.614	00.641	00.154	0.145	NA	0.150
Regulatory capital to risk-weighted assets	R2	0.416	00.617	00.095	0.110	NA	0.107
Regulatory Tier 1 capital to risk-weighted assets	R3	0.722	00.835	00.142	0.147	NA	0.124
Equity to debt	R4	1.500	11.789	00.175	0.169	NA	0.176
Financial leverage	R5	0.667	00.559	55.719	5.943	NA	5.701
NPL to total gross loans	R6	0.005	00.035	00.015	0.034	N/A	0.413
NPL to capital	R7	0.009	00.057	00.063	0.174	NA	3.163
Return on assets	R9	0.022	00.023	00.017	0.019	NA	0.003
Earnings before interest and taxes to assets	R11	0.050	00.023	00.053	0.063	NA	0.065
Net interest margin	R12	0.036	00.064	00.025	0.056	NA	0.041
Interest rate spread	R13	0.031	00.050	00.022	0.048	NA	0.008
Current liquidity ratio	R15	1.120	22.588	11.350	0.850	NA	1.134

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

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%

\*Sound groups are coloured in green, Risky in yellow and unsound group in red. \*\*Bank has been renamed.

## Appendix 1: Prior studies on the financial soundness of banks in Chronological order

Reference	The Purpose of the Study	Method Used	Country	Number of Observations	Findings
<b>Barth <i>et al.</i> (2002)</b>	This study estimates the association between banking performance, the structure of bank supervision, permissible banking activities, legal environments, banking market structure and macro- economic conditions.	Regression analysis, Ordinary least squares analysis.	70 countries	Country-wide analysis	Multiple supervisors usually reduce equity capital ratios and increase liquidity risk; Banks supervised by their central bank tend to have more nonperforming loans.
<b>Gasbarro <i>et al.</i> (2002)</b>	This study examines the financial soundness of Indonesian banks during the Southeast Asian financial crisis.	Panel data analysis.	Indonesia	52 banks	Changing importance of the CAMEL components during different economic conditions in Indonesia.
<b>Gaganis <i>et al.</i> (2006)</b>	This study develops a multicriteria model to classify banks into three groups depending on the level of their financial soundness.	UTADIS, Discriminant analysis, logit regressions.	79 countries	894 banks	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.
<b>Babihuga (2007)</b>	This study tests the relationship between macroeconomic variables and financial soundness indicators.	Panel data analysis.	96 countries	Country-wide analysis	Financial soundness indicators fluctuate strongly with the business cycle and the inflation rate.
<b>Čihák and Schaeck (2007)</b>	This study analyzes the aggregate banking system ratios, assess the power of these ratios in discriminating between sound and unsound banking systems.	Binomial logit regression model.	100 countries	Country-wide analysis	Aggregate bank ratios provide some indication of imbalance in banking system and have some benefit in determining the timing of crises.
<b>Ioannidis <i>et al.</i> (2010)</b>	This study classifies banks into groups for the creation of the early warning system to evaluate the soundness of individual banks.	MDA, UTADIS, ANN, k-NN, OLR, Stacked model.	78 countries	944 banks	Developed model that became more sophisticated when included the additional country-level variables and correctly classified even the banks with similar profiles.
<b>Bourkhis and Nabi (2013)</b>	This study evaluates the effect of the 2007–8 financial crisis on the soundness of Islamic banks and their conventional peers.	Regression analysis, Z-score.	16 countries	34 Islamic banks and 34 conventional banks	Determined no significant difference in the impact of the financial crisis on Islamic banks and conventional banks. Revealed that Islamic banks do not operate in accordance with their theoretical model, which would have allowed them to retain the level of financial soundness during the crisis.
<b>Navajas and Thegeya (2013)</b>	This study tests the effectiveness of financial soundness indicators as harbingers of banking crises.	Logit analysis.	80 countries	Country-wide analysis	Demonstrated that financial soundness indicators are contemporaneously correlated with the occurrence of banking crisis.
<b>Camelia and Angela (2013)</b>	This study examines the financial soundness of the banks operating in Central and Eastern Europe.	Quantitative analysis based on the CAMELS and Z-score.	Bulgaria, Czech Republic, Romania	40 commercial banks	Highest ranked banks are usually subsidiaries of the large pan-European banking groups, local knowledge and networking allow domestic banks to become very financially stable.

## Appendix 1: Prior studies on the financial soundness of banks (Continued)

Reference	The Purpose of the Study	Method Used	Country	Number of Observations	Findings
<b>Ginevičius and Podvezko (2013)</b>	This study evaluates the stability, dynamics, and soundness of Lithuanian commercial banks.	MCDA	Lithuania	8 banks	Discovered instability of the commercial banks market; banks' positions fluctuated significantly over the analyzed period.
<b>Kasselaki and Tagkalakis (2014)</b>	This study investigates the link between the financial soundness indicators and the financial crisis considering several macroeconomic and fiscal variables.	Regression analysis, two-step system GMM estimation.	20 OECD countries	Country-wide analysis	Found evidence that regulatory-capital-to-risk-weighted-assets increases as economic conditions worsen, whilst asset quality declines as NPL and banks' provisions to NPL increase due to deteriorating borrowers' creditworthiness and the value of collaterals.
<b>Ashraf and Tariq (2016)</b>	This study evaluates the ability of Bankometer model to detect the financial soundness of Pakistani listed banks compared to Z-score model.	Bankometer model and Z-score model.	Pakistan	Pakistani listed banks	Both models generally reported similar results.
<b>Chang (2016)</b>	This study examines the association between business cycle and bank soundness.	Probit regression estimation.	Taiwan	Country-wide analysis	Found that bank soundness worsened during contraction phase as well as expansion phase of real estate price, that is why ups and downs of real estate price should be monitored to prevent from banking fragility.
<b>Masud and Haq (2016)</b>	This study describes, measures, and ranks the financial situations of 5 private commercial banks using descriptive analysis.	Trend Analysis.	Bangladesh	5 private commercial banks	Most of the selected banks are in financially sound position. However, it is recommended that they should introduce different financial packages and technology to increase deposit collections and expand their business.
<b>Bitar et al. (2017)</b>	This study investigates whether and to what extent political systems affect the financial soundness of conventional and Islamic banks.	Principal component analysis.	33 countries	Conventional and Islamic banks	Found that Islamic banks underperform their conventional counterparts in Western and democratic political systems, but they show superior financial soundness in Sharia'a-based and hybrid legal systems.
<b>Rahman (2017)</b>	This study investigates the financial soundness of private commercial banks operating in Bangladesh using Bankometer model.	Bankometer model.	Bangladesh	24 private commercial banks (2010-2015).	Found that all the banks have ensured sound financial status individually and that the banking industry in Bangladesh has consistently been in favorable position during the period (2010-2015).



## Appendix 1: Prior studies on the financial soundness of banks (Continued)

Reference	The Purpose of the Study	Method Used	Country	Number of Observations	Findings
<b>Dash (2017)</b>	This study analyzes the financial soundness of the Indian banking system and compares the financial stability of public and private sector banks.	Z-score model and S-score model.	India	23 public and 16 private sector banks	Financial soundness of the private sector banks was determined to be significantly better than that of the public sector banks.
<b>Mittal and Mittal (2017)</b>	This study analyzes the financial soundness of private and public sector banks in India between 2007 and 2016.	Bankometer model.	India	13 private and 23 public banks	Concluded that observed private and public Indian banks are financially strong.
<b>Fernández-Arias et al. (2018)</b>	This study develops an early warning model that separates previously rated banks into three classes.	ANN, Extreme learning machine (ELM) combined with an oversampling technique (SMOTE).	28 countries	337 Fitch-rated banks	Confirmed the suitability and robustness of the proposed methodology, because it presents better performance rates than all other methods tested (80.05% correct classification).
<b>AlAli and Al-Yatama (2019)</b>	This study evaluates the financial soundness of Kuwaiti banks that are listed at Kuwait stock exchange over the period 2011-2016.	CAMELS framework	Kuwait	9 banks (2011-2016).	Ahli united bank was the top performing bank in Kuwait during the study period despite showing weakness in terms of capital adequacy and liquidity while the worst performing bank was Kuwait finance house.
<b>Bae (2019)</b>	This study analyzes the determinants of financial Soundness of savings banks.	Panel Fixed effect model	South Korea	693 observations	It is not easy for a savings bank to build an aggressive loan portfolio in South Korea where the relationship between lending rate and NPL ratio is negative and highly significant.
<b>Ouma and Kirori (2019)</b>	This study investigates the financial soundness of small and medium-sized commercial banks in Kenya for the years 2014 to 2017.	Bankometer model	Kenya	12 medium-sized and 16 small banks	Both small and medium-sized commercial banks in Kenya were financially sound during each of the four years studied with no significant differences in the financial soundness of the two bank categories. All the banks studied experienced poor performance in loans and operations while two banks had below the benchmark capital adequacy ratio.

## Appendix 1: Prior studies on the financial soundness of banks (Continued)

Reference	The Purpose of the Study	Method Used	Country	Number of Observations	Findings
<b>Seyedi and Abdoli (2019)</b>	This study identifies and prioritizes the factors affecting the financial soundness of Iranian banks.	Questionnaire, descriptive-correlation, confirmatory factor analysis, TOPSIS method.	Iran	382 banking experts in Iran	The findings showed that capital adequacy, asset quality, profitability, liquidity, management quality, sensitivity to market risk, Islamic banking, corporate governance, and facilities with technical and economic backing affect the financial soundness of banks, where liquidity and profitability indexes have the most impact.
<b>Suresh <i>et al.</i> (2019)</b>	This study investigates the financial performance of Bank of Bhutan Limited (BOB) and Tashi Bank (T-Bank) using DuPont Analysis.	DuPont analysis and Bankometer model.	Bhutan	Two banks over the period 2012 to 2017.	Both banks had ensured financial performance and financial soundness.
<b>Talibong and Simiyu (2019)</b>	This study identifies the influence of financial soundness indicators on the financial performance of deposit taking microfinance banks in Kenya.	Panel data regression.	Kenya	13 Deposit Taking microfinance banks licensed and regulated by the CBK over the period 2012 to 2017.	The results indicate that capital adequacy, asset quality, liquidity, sustainability financial cover and investment growth were able to explain 68.43% of the variation in the financial performance of deposit taking microfinance banks in Kenya.
<b>Nosheen and Rashid (2020)</b>	This study investigates the financial stability of the countries having both Islamic and conventional banks versus the countries having conventional banks only.	Panel data regression.	39 countries	416 banks drawn from 39 countries over the period 1995–2014.	The results provide sound evidence that the dual banking system is more stable than the single banking system. Higher stability is attributed to the presence of Islamic banks in the dual banking system. Furthermore, when only the dual banking system is investigated, the results strongly confirm the greater stability of Islamic banks as compared to their conventional counterparts.

## Appendix 2: Sample distribution

Year	Number of banks
2008	34
2009	36
2010	37
2011	38
2012	37
2013	37
2014	37
Total bank-year observations	256

### Appendix 3: The financial ratios employed in the current study

	Code	Ratio	Measurement	References
Capital Adequacy	RR1	Capital adequacy ratio (CAR)	Equity / Total Assets.	e.g., Estrella <i>et al.</i> , 2000; Babihuga, 2007; Dermine, 2015; Bitar <i>et al.</i> , 2017; and Ouma and Kirori, 2019.
	RR2	Regulatory capital to risk-weighted assets	Regulatory Capital / Risk-Weighted Assets.	e.g., Čihák and Schaeck, 2007; Michalak and Uhde, 2012; and Navajas and Thegeya, 2013.
	RR3	Regulatory Tier 1 capital to risk-weighted assets	Tier 1 Regulatory Capital / Risk Weighted Assets.	e.g., Chauhan <i>et al.</i> , 2009; Ravi and Pramodh, 2008; Chiaramonte and Casu, 2013; Bitar <i>et al.</i> , 2017; and Ouma and Kirori, 2019.
	RR4	Equity to debt ratio	Book Value of Equity / Book Value of Long-term Debts.	e.g., Vaziri <i>et al.</i> , 2012; Rankov and Kotlica, 2013; and Hogan, 2015.
	RR5	Financial leverage	Total Liabilities / Total Equity.	e.g., Čihák and Schaeck, 2007; Miller <i>et al.</i> , 2015; and Bitar <i>et al.</i> , 2017.
Asset Quality	RR6	Nonperforming loans to total gross loans ratio	Value of NPLs / Total Value of the Loan Portfolio.	e.g., Barth <i>et al.</i> , 2002; Navajas and Thegeya, 2013; Rashid and Rustam, 2015; Ouma and Kirori, 2019; and Liu <i>et al.</i> , 2020.
	RR7	Nonperforming loans net of provisions to capital ratio	(NPLs - the Value of Specific Loan Provisions) / Total Regulatory Capital.	e.g., Barth <i>et al.</i> , 2002; Othman, 2013; Rashid and Rustam, 2015; and Liu <i>et al.</i> , 2020.
Management	RR8	Salary to assets ratio	Gross Salary Accrued / Total Assets.	Tuymenbayeva (2014).
Earnings	RR9	Return on assets (ROA)	Earnings after Tax / Total Assets.	e.g., Flannery and Sorescu, 1996; Babihuga, 2007; and Diaconu and Oanea, 2014.
	RR10	Return on equity (ROE)	(Gross Income - Gross Expenses) / Average Value of Capital.	e.g., Babihuga, 2007; Čihák and Schaeck, 2007; Navajas and Thegeya, 2013; and Kliestik <i>et al.</i> , 2020.
	RR11	EBIT to total assets ratio	Earnings Before Interest and Tax / Total Assets.	e.g., Ravi and Pramodh, 2008; Chauhan <i>et al.</i> , 2009; and Hogan, 2015.
	RR12	Net interest margin	(Interest Income - Interest Expenses) / Earning Assets.	Rashid and Rustam (2015).
	RR13	Interest rate spread	Lending Rate – Deposit Rate.	e.g., Safdari <i>et al.</i> , 2005; and Rashid and Rustam, 2015.
Liquidity	RR14	Working capital to total assets ratio	(Current Assets – Current Liabilities) / Total Assets.	e.g., Ozkan-Gunay and Ozkan, 2007; Ravi and Pramodh, 2008; Vaziri <i>et al.</i> 2012; and Hogan, 2015.
	RR15	Current ratio	Average Current Assets / Average Demand Deposit Liabilities.	e.g., Ozkan-Gunay and Ozkan, 2007; Chiaramonte and Casu, 2013; and Kliestik <i>et al.</i> , 2020.

## Appendix 4: Prior studies on cluster analysis in Chronological order

Reference	The Purpose of the Study	Methods Used	Country	Results
Alam <i>et al.</i> (2000)	To identify potentially failing banks.	Cluster Analysis	USA	Both the fuzzy clustering and self-organizing neural networks seek to give classification tools for identifying potentially failing banks.
Safdari <i>et al.</i> (2005)	To develop a methodology for peer group determination.	Factor and Cluster Analyses	Republic of Armenia	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.
Dardac and Boitan (2009)	To assess the risk profile and profitability of financial institutions.	Cluster Analysis	Romania	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)	To identify the profile of bank customers.	Cluster Analysis, PCA	Germany	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 <i>et al.</i> (2011)	To model the risk patterns of Russian Systemically Important Financial Institutions (SIFI).	Cluster Analysis, Copula Models	Russia	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.
Abudu (2011)	To predict bank failure.	Cluster Analysis	USA	Proposed a 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.
Peresetsky <i>et al.</i> (2011)	To present an econometric analysis of Russian bank defaults during the period 1997–2003.	Cluster, Logit and Probit Analysis.	Russia	Found that automatic clustering improves the predictive power of the models.
Paradi <i>et al.</i> (2012)	To identify managerial groups in a large Canadian bank branch network.	DEA and Cluster Analysis	Canada	Proposed a new grouping approach in a DEA framework designed to identify bank branch management groups. This approach 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)	To test the ability of cluster analysis to recognize vulnerable banks and their common characteristics.	Cluster and PCA	Vietnam	Found that cluster analysis helps identify vulnerable banks in the crisis. ROA, ROE, and Equity capital to assets ratios can be the warning indicators.
Türkcs (2017)	To evaluate the level of total assets and continental banking markets degree of differentiation banks.	Cluster and Descriptive Analysis	Cross-country	The results indicate that the largest portion of total banking assets is concentrated in Asia and the smallest is in Africa. At the end of 2016, the top 16 global banks owned assets totalling \$ 30.19 trillion according to the data set contains cluster 1 and the centroid was (2.25, 2.11, 3.06, 0.01).
Affes and Hentati-Kaffel (2019)	To model the relationship between ten financial variables and financial distress.	Clustering and MARS model	USA	Hybrid model which combines K-means clustering and MARS enhanced the classification accuracy for the training sample.
Cyree <i>et al.</i> (2020)	To identify appropriate peer groups of commercial banks based on their financial structure.	Cluster and Descriptive Analysis	Cross-country	Bank clusters are formed largely around loan types, funding differences, and management's strategic choices. These bank clusters are shown to have substantially greater explanatory power in regression models when compared to groupings based on bank size in several different years.
Huang <i>et al.</i> (2020)	To introduce the Kernel method into fuzzy c-mean algorithm (FCM) and synthetic minority over-sampling technique (SMOTE) and combine them with support vector machine (SVM) to propose a hybrid model of KFCM-KSMOTE-SVM for predicting extreme financial risks.	KFCM-KSMOTE-SVM and Cluster analysis	China	The results showed that KFCM-KSMOTE-SVM outperforms other various prediction models significantly. It can solve the class imbalance problem in financial markets and is more appropriate for predicting extreme financial risks.
Liu <i>et al.</i> (2020)	To demonstrate the FPCA and clustering pattern of NPLs and government debt for 25 EU and BRICS countries.	FPCA and Cluster Analysis	Cross-country	The results demonstrated that the government debt markets of EU countries experienced a similar trend in terms of NPLs, with a similar size of NPLs across debt markets.

**Appendix 5: Correlation matrix**

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
R1	1														
R2	0.986**	1													
R3	0.607**	0.626**	1												
R4	0.191**	0.203**	0.077	1											
R5	-0.66**	-0.638**	-0.481**	-0.103	1										
R6	-0.338**	-0.342**	-0.248**	-0.050	0.067	1									
R7	-0.127*	-0.123*	-0.119	-0.020	0.224**	0.498**	1								
R8	0.306**	0.307**	0.175**	0.004	-0.288**	-0.059	-0.064	1							
R9	0.286**	0.273**	0.115	-0.004	0.224**	-0.328**	0.103	-0.050	1						
R10	-0.204**	-0.216**	-0.118	-0.016	0.056	0.247**	0.068	-0.031	0.272**	1					
R11	0.142*	0.129*	-0.031	-0.025	0.274**	-0.236**	0.146*	-0.059	0.922**	0.362**	1				
R12	0.197**	0.143*	-0.065	-0.063	-0.199**	-0.098	-0.075	0.122	0.118	-0.062	0.097	1			
R13	0.140*	0.087	-0.082	-0.062	-0.143*	-0.212**	-0.146*	0.142*	0.123*	-0.073	0.097	0.936**	1		
R14	0.262**	0.251**	0.264**	0.020	-0.257**	-0.023	0.005	0.158*	0.010	0.031	-0.004	0.064	0.058	1	
R15	0.164**	0.173**	0.093	0.204**	-0.092	-0.043	-0.017	0.073	0.005	-0.010	-0.011	-0.022	-0.054	0.021	1

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

## Appendix 6: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		0.635
Bartlett's Test of Sphericity	Approximate Chi-Square	2861.467
	Degrees of freedom	105
	P-values	0.000

## Appendix 7: Total Variance Explained (Principal Components)

Component	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	3.696	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	0.81	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	99.23						
13	0.057	0.381	99.611						
14	0.047	0.314	99.925						
15	0.011	0.075	100						

## Appendix 8: Rotated Component Matrix

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

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



## Appendix 9: A Comparison between bank's rank and cluster<sup>i</sup>

2008		2013		2014	
Bank name*	Average ranking Score	Bank name*	Average ranking Score	Bank name*	Average ranking Score
Masterbank (dissolved)	7.42	SB PNB Kazakhstan	7,25	SB PNB Kazakhstan	7.75
SB Bank of China in Kazakhstan	6.58	SB KZI Bank	7,17	SB NB of Pakistan in Kazakhstan	7.58
Senim-Bank (Qazaq Banki)**	6.33	Al Hilal Islamic Bank	7,08	Zaman Bank	7.08
SB Lariba-Bank (AsiaCredit Bank)**	6.33	SB NB of Pakistan in Kazakhstan	6,83	SB KZI Bank	6.58
Zaman-Bank	6.17	Shinhan Bank of Kazakhstan	6,67	Al Hilal Islamic Bank	6.58
TPBK	6.17	SB Home Credit and Finance Bank	6,50	Shinhan Bank Kazakhstan	6.58
Express Bank (dissolved)	5.75	SB Taib Kazakh Bank	6,17	SB Home Credit Bank	6.17
SB NB of Pakistan in Kazakhstan	5.50	Zaman-Bank	6,08	Bank Positive Kazakhstan	5.58
SB Alfa-Bank	5.50	Bank Positive Kazakhstan	5,67	SB Taib Kazakh Bank	5.58
SB Taib Kazakh Bank	5.33	TPBK	5,50	SB RBS Kazakhstan	4.83
Kazinkombank (Bank RBK)**	5.25	Qazaq Banki	5,42	Bank Kassa Nova	4.83
SB Sberbank of Russia	5.25	Bank Kassa Nova	5,25	Eximbank Kazakhstan	4.75
Delta Bank	5.17	Kaspi Bank	4,58	ForteBank	4.67
Eximbank Kazakhstan	5.17	AsiaCredit Bank	4,50	AsiaCredit Bank	4.67
Metrokombank (ForteBank)**	5.00	Eximbank Kazakhstan	4,42	Kaspi Bank	4.42
MB Alma-Ata (Home Credit Bank) **	4.92	Bank RBK	4,42	Delta Bank	4.33
Alliance Bank	4.83	ForteBank	4,33	TPBK	4.17
Kazinvestbank	4.83	Delta Bank	4,33	Bank Astana-Finance	4.17
SB KZI Bank	4.67	SB VTB Bank Kazakhstan	4,33	SB Alpha Bank	4.17
Demir Kazakhstan Bank (Bank Positive Kazakhstan) **	4.67	Eurasian Bank	4,25	SB Bank of China in Kazakhstan	4.17
Danabank (SB PNB Kazakhstan)**	4.58	SB Alpha-Bank	4,25	Eurasian Bank	4.17
Bank Turanalem (BTA Bank) **	4.50	SB Bank of China in Kazakhstan	4,25	SB Sberbank of Russia	4.17
Nurbank	4.42	Tsesnabank	4,17	Kazkommertsbank	4.08
Temirbank	4.42	Bank Astana-Finance	4,17	Halyk Bank of Kazakhstan	4.00
SB ABN Amro Bank (SB RBS Kazakhstan) **	4.25	SB Sberbank of Russia	4,17	Citibank Kazakhstan	4.00
Bank CenterCredit	4.17	SB RBS Kazakhstan	4,17	SB HSBC Bank Kazakhstan	3.92
Eurasian Bank	4.17	Kazkommertsbank	4,00	SB VTB Bank Kazakhstan	3.92
Citibank Kazakhstan	4.08	SB HSBC Bank Kazakhstan	3,92	Qazaq Banki	3.92
Tsesnabank	4.08	Halyk Bank of Kazakhstan	3,92	Bank RBK	3.83
SB HSBC Bank Kazakhstan	4.00	Citibank Kazakhstan	3,83	Tsesnabank	3.83
ATF Bank	3.83	Bank Centercredit	3,75	Bank CenterCredit	3.75
Halyk Bank of Kazakhstan	3.83	Alliance Bank	3,67	Kazinvestbank	3.75
Bank Caspian (Kaspi Bank) **	3.75	Nurbank	3,50	Temirbank	3.50
Kazkommertsbank	3.67	Kazinvestbank	3,50	BTA Bank	3.25
		ATF Bank	3,50	ATF Bank	3.08
		Temirbank	3,00	Nurbank	3.00
		BTA Bank	1,83	Alliance Bank	2.50

\*Sound groups are coloured in green, Risky in yellow and unsound group in red. \*\*Bank has been renamed.

## References

- Abudu, B. (2011), "Cluster-Based Classification Approaches to Bank Failure", Ph.D. thesis. University of Essex, Essex.
- Alam, P., Booth, D., Lee, K. and Thordarson, T. (2000), "The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: an experimental study", *Expert Systems with Applications*, Vol. 18 No. 3, pp. 185-199.
- AlAli, M. and Al-Yatama, S. (2019), "Analyzing the Financial Soundness of Kuwaiti Banks Using CAMELS Framework", *Financial Risk and Management Reviews*, Vol. 5 No. 1, pp. 55-69.
- Affes, Z. and Hentati-Kaffel, R. (2019), "Forecast bankruptcy using a blend of clustering and MARS model: case of US banks", *Annals of Operations Research*, Vol. 281 No. 1-2, pp. 27-64.
- Ashraf, A. and Tariq, Y. (2016), "Evaluating the financial soundness of banks: An application of Bankometer on Pakistani listed banks", *The IUP Journal of Financial Risk Management*, Vol. 13 No. 3, pp. 47-63.
- Babihuga, R. (2007), "Macroeconomic and Financial Soundness Indicators: An Empirical Investigation", No. 7-115. International Monetary Fund.
- Bae, S.H. (2019), "A study on determinants of financial soundness of savings banks", *The Journal of the Convergence on Culture Technology*, Vol. 5 No. 4, pp.277-282.
- Barth, J., Dopico, L., Nolle, D. and Wilcox, J. (2002), "Bank Safety and Soundness and the Structure of Bank Supervision: A Cross-Country Analysis", *International Review of Finance*, Vol. 3 No. 3-4, pp. 163-188.
- Bitar, M., Hassan, M. and Walker, T. (2017), "Political systems and the financial soundness of Islamic banks", *Journal of Financial Stability*, Vol. 31, pp. 18-44.
- Bourkhis, K. and Nabi, M. (2013), "Islamic and conventional banks' soundness during the 2007–2008 financial crisis", *Review of Financial Economics*, Vol. 22 No. 2, pp. 68-77.
- Camelia, Ş.A. and Angela, R. (2013), "A cross-country analysis of the banks' financial soundness: The case of the CEE-3 countries", *Economic Science*, Vol. 22 No. 1, pp. 357-367.
- Chang, Y. (2016), "Financial soundness indicator, financial cycle, credit cycle and business cycle - Evidence from Taiwan", *International Journal of Economics and Finance*, Vol. 8 No. 4, pp. 166-182.
- Chauhan, N., Ravi, V. and Chandra, D. (2009), "Differential evolution trained wavelet neural networks: Application to bankruptcy prediction in banks", *Expert Systems with Applications*, Vol. 36 No. 4, pp. 7659-7665.
- Chiaromonte, L. and Casu, B. (2013), "The determinants of bank CDS spreads: Evidence from the financial crisis", *European Journal of Finance*, Vol. 19 No. 9, pp. 861-887.
- Čihák, M. and Schaeck, K. (2007), "How well do aggregate bank ratios identify banking problems?", No. 7-275. International Monetary Fund.
- Cyree, K.B., Davidson, T.R. and Stowe, J.D. (2020), "Forming appropriate peer groups for bank research: A cluster analysis of bank financial statements", *Journal of Economics and Finance*, Vol. 44 No. 2, pp.211-237.

- Dao, B. and Khanh, P. (2014), "Cluster analysis of Vietnamese banks", *Available at SSRN 2543094*.
- Dardac, N. and Boitan, I. (2009), "A cluster analysis approach for bank's risk profile: The Romanian evidence", *European Research Studies Journal*, Vol. 12 No. 1, pp. 109-118.
- Dash, M. (2017), "Comparison of financial soundness of public and private sector banks in India using the S-score model", *Skyline Business Journal*, Vol. 12 No. 1, pp. 64-75.
- Dermine, J. (2015), "Basel III leverage ratio requirement and the probability of bank runs", *Journal of Banking & Finance*, Vol. 53, pp. 266-277.
- Diaconu, R. and Oanea, D. (2014), "The main determinants of bank's stability: Evidence from Romanian banking sector", *Procedia Economics and Finance*, Vol. 16, pp. 329-335.
- Estrella, A., Park, S. and Peristiani, S. (2000), "Capital ratios as predictors of bank failure", *Economic Policy Review*, Vol. 6 No. 2, pp. 33-52.
- Fernández-Arias, D., López-Martín, M., Montero-Romero, T., Martínez-Estudillo, F. and Fernández-Navarro, F. (2018), "Financial soundness prediction using a multi-classification model: Evidence from current financial crisis in OECD banks", *Computational Economics*, Vol. 52 No. 1, pp. 275-297.
- Flannery, M. and Sorescu, S. (1996), "Evidence of bank market discipline in subordinated debenture yields: 1983-1991", *The Journal of Finance*, Vol. 51 No. 4, pp. 1347-137.
- Gaganis, C., Pasiouras, F. and Zopounidis, C. (2006), "A multicriteria decision framework for measuring banks' soundness around the world", *Journal of Multi-Criteria Decision Analysis*, Vol. 14 No. 1-3, pp. 103-111.
- Gasbarro, D., Sadguna, I. and Zumwalt, J. (2002), "The changing relationship between CAMEL ratings and bank soundness during the Indonesian banking crisis", *Review of Quantitative Finance and Accounting*, Vol. 19 No. 3, pp. 247-260.
- Ginevičius, R. and Podviekzo, A. (2013), "The evaluation of financial stability and soundness of Lithuanian banks", *Economic Research-Ekonomska Istraživanja*, Vol. 26 No. 2, pp. 191-208.
- Hogan, T. (2015), "Capital and risk in commercial banking: A comparison of capital and risk-based capital ratios", *The Quarterly Review of Economics and Finance*, Vol. 57, pp. 32-45.
- Huang, X., Zhang, C. and Yuan, J. (2020), "Predicting extreme financial risks on imbalanced dataset: A combined Kernel FCM and Kernel SMOTE based SVM classifier", *Computational Economics*, pp. 1-30. DOI: [10.1007/s10614-020-09975-3](https://doi.org/10.1007/s10614-020-09975-3).
- Ioannidis, C., Pasiouras, F. and Zopounidis, C. (2010), "Assessing bank soundness with classification techniques", *Omega*, Vol. 38 No. 5, pp. 345-357.
- Kasselaki, M. and Tagkalakis, A. (2014), "Financial soundness indicators and financial crisis episodes", *Annals of Finance*, Vol. 10 No. 4, pp. 623-669.
- Kliestik, T., Valaskova, K., Lazaroiu, G., Kovacova, M. and Vrbka, J. (2020), "Remaining financially healthy and competitive: The role of financial predictors", *Journal of Competitiveness*, Vol. 12 No. 1, pp. 74-92.
- Liu, L., Liu, Y. and Kim, J. (2020), "Sustainable visual analysis for bank non-performing loans and government debt distress", *Sustainability*, Vol. 12 No. 1, pp. 131. <https://doi.org/10.3390/su12010131>.

- Masud, A. and Haq, M. (2016), "Financial soundness measurement and trend analysis of commercial banks in Bangladesh: An observation of selected banks", *European Journal of Business and Social Science*, Vol. 4 No. 10, pp. 159-184.
- Michalak, T. and Uhde, A. (2012), "Credit risk securitization and bank soundness in Europe", *The Quarterly Review of Economics and Finance*, Vol. 52 No. 3, pp. 272-285.
- Miller, S., Olson, E. and Yeager, T. (2015), "The relative contributions of equity and subordinated debt signals as predictors of bank distress during the financial crisis", *Journal of Financial Stability*, Vol. 16, pp. 118-137.
- Mittal, S. and Mittal, M. (2017), "Assessment of financial soundness of private and public sector banks in India", *Research Review International Journal of Multidisciplinary*, Vol. 2 No. 9, pp. 72-75.
- Navajas, M. and Thegeya, A. (2013), "*Financial Soundness Indicators and Banking Crises*", No. 13-263. International Monetary Fund.
- Nosheen, and Rashid, A. (2020), "Financial soundness of single versus dual banking system: explaining the role of Islamic banks", *Portuguese Economic Journal*, Vol 19 No.1, pp.1-29. DOI: <https://link.springer.com/article/10.1007%2Fs10258-019-00171-2>
- Othman, J. (2013), "*Analysing Financial Distress in Malaysian Islamic Banks: Exploring Integrative Predictive Methods*", Ph.D. thesis, Durham University, Durham.
- Ouma, M.O. and Kirori, G.N. (2019), "Evaluating the financial soundness of small and medium-sized commercial banks in Kenya: an application of the bankometer model", *International Journal of Economics and Finance*, Vol. 11 No. 6, pp. 1-93.
- Ozkan-Gunay, E. and Ozkan, M. (2007), "Prediction of bank failures in emerging financial markets: an ANN approach", *The Journal of Risk Finance*, Vol. 8 No. 5, pp. 465-480.
- Paradi, J., Zhu, H. and Edelstein, B. (2012), "Identifying managerial groups in a large Canadian bank branch network with a DEA approach", *European Journal of Operational Research*, Vol. 219 No. 1, pp. 178-187.
- Penikas, H., Aivazian, S., Connolly, R. and Andrievskaya, I. (2011), "Modeling risk patterns of Russian systemically important financial institutions", *Review of Applied Socio-Economic Research*, Vol. 1 No. 1, pp. 70-80.
- Peresetsky, A., Karminsky, A. and Golovan, S. (2011), "Probability of default models of Russian banks", *Economic Change and Restructuring*, Vol. 44 No. 4, pp.297-334.
- Rahman, Z. (2017), "Financial Soundness Evaluation of Selected Commercial Banks in Bangladesh: An Application of Bankometer Model", *Research Journal of Finance and Accounting*, Vol. 8 No. 2, pp. 63-70.
- Rankov, S. and Kotlica, S. (2013), "Bankruptcy prediction model used in credit risk management", *Megatrend Review*, Vol. 10 No. 4, pp. 37-58.
- Rashid, K. and Rustam, A. (2015), "A comparative study of the performance of local and foreign banks in pakistan: Some ANOVA evidence", *The IUP Journal of Bank Management*, Vol. 14 No. 1, pp. 7-20.
- Ravi, V. and Pramodh, C. (2008), "Threshold accepting trained principal component neural network and feature subset selection: Application to bankruptcy prediction in banks", *Applied Soft Computing*, Vol. 8 No. 4, pp. 1539-1548.

Safdari, C., Scannell, N. and Ohanian, R. (2005), "A statistical approach to peer-groupings; the case of banks in Armenia", *Journal of American Academy of Business*, Vol. 6 No. 2, pp. 24-31.

Şchiopu, D. (2010), "Applying TwoStep cluster analysis for identifying bank customers' profile", *Economic Sciences Series*, Vol. 62 No. 3, pp. 66-75.

Seyedi, S.A. and Abdoli, M.R. (2019), "Modeling and rating financial soundness indicators of commercial banks using confirmatory factor analysis and TOPSIS method", *Iranian Journal of Finance*, Vol. 3 No. 3, pp.107-136.

Suresh, N., Ligori, A., Khan, S. and Khan, S.A. (2019), "Comparative financial performance and financial soundness of banks in Bhutan: Application of Dupont and bankometer models", *International Journal of Psychosocial Rehabilitation*, Vol. 23 No. 1, pp. 441-448.

Talibong, J.K. and Simiyu, E.M. (2019), "Financial soundness indicators and financial performance of deposit taking micro finance banks in Kenya", *African Journal of Emerging Issues*, Vol. 1 No. 11, pp.67-84.

Tuymenbayeva, O. (2014), "*The Restructuring of the Kazakh Banks in the Financial Crisis: Theory and Practice*" Ph.D. thesis, Kazakh Economic University, Almaty.

Türkes, M. (2017), "Cluster analysis of total assets provided by banks from four continents", *Academic Journal of Economic Studies*, Vol. 3 No. 4, pp. 24-28.

Vaziri, M., Bhuyan, R. and Manue, P. (2012), "Comparative predictability of failure of financial institutions using multiple models", *Investment Management and Financial Innovations*, Vol. 9 No. 2, pp. 120-127.

## Endnotes

---

<sup>i</sup> The number of banks in 2008 was 34, and 37 in both 2013 and 2014. Two banks were dissolved (Masterbank and Express Bank) in 2008 and five new banks appeared in 2013. These are Al Hilal Islamic Bank, Shinhan Bank Kazakhstan, Bank Kassa Nova, Bank Astana-Finance, and SB VTB Bank Kazakhstan.