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ӘЛЕУМЕТТІК-ЭКОНОМИКАЛЫҚ ЖҮЙЕЛЕРДІ ДАМЫТУДАҒЫ ЦИФРЛЫҚ ТЕХНОЛОГИЯЛАР

АҚПАРАТТЫҚ ТЕХНОЛОГИЯЛАР

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CREDIT RISK MANAGEMENT OF "HALYK BANK" JSC: PROBLEMS AND SOLUTIONS

A.Y. Azharbayeva[1]*, M.Kh. Abdinova[2], I. Khlevna[3]

Azharbayeva Aida Yeseninkyzym — student of the "Economics and Business" department, International Information Technology University
ORCID: 0009-0001-0297-8542. E-mail: aida.azharbaeva2015@gmail.com;
Abdinova Makpal Khamitkhanovna — senior lecturer of the "Economics and Business" department, International Information Technology University
ORCID: 0000-0002-7482-5609.
I. Khlevna — professor, Taras Shevchenko National university of Kyiv (Ukraine)

Abstract. The purpose of the research work is to reveal the essence of the credit risk system, study the causes of its occurrence, and conduct a detailed analysis of the loan portfolio and credit risk management methods on the example of the commercial bank "Halyk Bank of the Republic of Kazakhstan" JSC. The authors analyze the loan portfolio of the bank using CAMELS, Z - score methods and build a regression analysis using R-studio, identify the main problems in credit risk management in a commercial bank and propose some solutions. In this article such problems in credit risk management as incomplete credit risk assessment, weak credit risk monitoring, insufficient collateral assessment, improper risk diversification, insufficient credit risk management policy are identified, and several solutions and methods for their improvement are proposed. The informational approach to solving the set goals is formed based on existing scientific research, published periodicals, scientific articles and financial statements of the bank, and its statistical data is used as material for writing a research paper.

Keywords: credit risk, Z-score, regression analysis, CAMELS approach, credit risk management

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"ХАЛЫҚ БАНКІ" АҚ КРЕДИТТІК ТӘУЕКЕЛДЕРДІН БАСҚАРУ: МӘСЕЛЕЛЕРІ ЖӘНЕ ШЕШУ ЖОЛДАРЫ

А.Е. Ажарбаева[1]*, М.Х. Абдинова[2], I. Khlevna[3]

Ажарбаева Аида Есенинқызы — "Экономика және Бизнес" кафедрасының студенті,
Халықаралық Ақпараттық Технологиялар Университеті
ORCID: 0009-0001-0297-8542;
Абдинова Мақпал Хамитханқызы — "Экономика және Бизнес" кафедрасының сеньор-лекторы,
Халықаралық Ақпараттық Технологиялар Университеті
ORCID: 0000-0002-7482-5609.
I. Khlevna — Профессор, Тарас Шевченко Атындағы Киев Ұлттық университеті (Украина)

Аннотация. Зерттеу жұмысының мақсаты кредиттік тәуекел жүйесінің мә нін ашу және оның туындау себептерін зерделеу, сондай-ақ "Қазақстан Республикасының Халық банкі" АҚ коммерциялық банкі мысалында кредиттік портфельді және кредиттік тәуекелді басқару әдістерін талдау болып табылады. Camels, Z — score әдістерін қолдана отырып, банктің несиелік портфелін талдау және R-studio көмегімен регрессиялық талдау жасау. Коммерциялық банктегі несиелік тәуекелді басқару процесіндегі негізгі мәселелерді анықтап, оларды шешу дің бірнеше жолдары мен әдістерін ұсыну. Бұл мақалада несиелік тәуекелді басқару процесінде несиелік тәуекелді бағалаудың келесідей несиелік тәуекелді бақылаудың әлсіздігі, кепілдікті бағалаудың жеткіліксіздігі, тәуекелдерді әр-тарап тандырудың жеткіліксіздігі, несиелік тәуекелді басқару саясатының жет-кіліксіздігі сияқты негізгі проблемалар анықталды және оларды жақсартудың бірнеше шешімдері мен әдістері ұсынылды. Қойылған мақсаттарды шешудің ақпараттық тәсілі зерттелген ғылыми зерттеулердің, мерзімді басылымдардың, ғылыми мақалалардың және зерттелетін банктің қаржылық есептілігінің негізінде қалыптасты және оның статистикалық деректері зерттеу жұмысын жазу үшін материал ретінде де пайдаланылды.

Түйін сөздер: несиелік тәуекел, Z-score, регрессиялық талдау, түйелер тәсілі, несиелік тәуекелді басқару

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УПРАВЛЕНИЕ КРЕДИТНЫМИ РИСКАМИ АО «НАРОДНЫЙ БАНК»: ПРОБЛЕМЫ И ПУТИ РЕШЕНИЯ

А.Е. Ажарбаева[1]*, М.Х. Абдинова[2], I. Khlevna [3]

Ажарбаева Аида Есенинқызы — студент кафедры «Экономики и Бизнеса», Международный Университет Информационных Технологий
ORCID: 0009-0001-0297-8542;
Абдинова Макпал Хамитхановна — сеньор-лектор кафедры «Экономики и Бизнеса», Международный Университет Информационных Технологий
ORCID: 0000-0002-7482-5609.
I. Khlevna — профессор Киевского национального университета имени Тараса Шевченко (Украина)

Аннотация. Целью исследовательской работы является раскрытие сущности системы кредитного риска и изучение причин его возникновения, а также детальный анализ кредитного портфеля и методов управления кредитным риском на примере коммерческого банка АО "Народный банк Республики Казахстан". Авторы предприняли попытку проанализировать кредитный портфель банка с помощью методов CAMELS, Z – score, построить регрессионный анализ с помощью R-studio, выявить основные проблемы в управлении кредитным риском в коммерческом банке и предложить пути их решения. В данной статье были выявлены основные проблемы в процессе управления кредитным риском, такие как неполноценная оценка кредитного риска, слабый мониторинг кредитного риска, недостаточная оценка обеспечения, неправильная диверсификация рисков, недостаточная политика управления кредитным риском и предложено несколько решений и методов улучшения работы. Информационный подход к решению поставленных целей был сформирован на основе имеющихся научных исследований, опубликованных периодических изданий, научных статей и финансовой отчетности исследуемого банка, а его статистические данные были использованы в качестве материала для написания исследовательской работы.

Ключевые слова: кредитный риск, Z-score, регрессионный анализ, подход CAMELS, управление кредитным риском

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Introduction

Credit risk management is an essential aspect of financial management that involves evaluating, monitoring, and controlling potential credit risks a company or financial institution faces. The management of credit risk is crucial for ensuring the stability and profitability of an organization by minimizing the possibility of default or non-payment of loans or credit facilities.

Credit risk management should be primarily related not to the fight against losses in the banking sector, but to implementing activities to create a system that will ensure the realization of the interests of the lender and the borrower (Kuznetsova, 2017). Thus, credit risk management is one of the most important tasks for the financial liquidity and stability of the banking sector due to the increased sensitivity of banks to credit risks and changes in the development of prices for financial instruments (Andrianova, 2013).

Halyk Bank, one of Kazakhstan's largest banks, employs various credit risk management techniques to mitigate potential losses. The bank conducts a thorough credit assessment process to evaluate the creditworthiness of its borrowers and maintains strict lending standards. Additionally, Halyk Bank regularly monitors its loan portfolio and takes prompt action to address any signs of potential default. The bank also diversifies its loan portfolio to spread its credit risk across different sectors and borrowers (Halyk Bank of Kazakhstan JSC, Almaty, 2021).

Materials and methods

Credit risk analysis

Altman's Z-score model is a statistical tool used to predict the likelihood of a company's bankruptcy based on its financial statements. This model is widely used in finance and accounting to assess credit risk and is particularly relevant for banks and other financial institutions. The model uses a set of financial ratios to calculate a score that represents the probability of a company's bankruptcy within the next two years. The higher the score, the lower the probability of bankruptcy.

The formula for Altman's Z-score model is as follows:

Z-score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E

where:

A = Working Capital / Total Assets

B = Retained Earnings / Total Assets

C = Earnings Before Interest and Taxes (EBIT) / Total Assets

D = Market Value of Equity / Total Liabilities

E = Sales / Total Assets

Table 1 – "Altman's Z-score model"

Altman's Z-score model					
	2022	2021	2020	2019	2018
A	-0.055735	-0.06985	-0.038655	-0.09338	-0.135558
B	0.136588	0.133552	0.133764	0.130914	0.107848
C	0.073052	0.058588	0.055848	0.06198	0.060999
D	4.462336	4.099301	3.961967	4.211203	3.366296
E	0.087179	0.072768	0.070586	0.076916	0.076129
Z-score	3.130	2.829	2.773	2.879	2.286
Created by the author based on the own calculations.					

Altman's Z-score is a financial ratio that is used to assess a company's financial health and creditworthiness. A Z-score above 3.0 is generally considered to indicate a low risk of bankruptcy, while a score below 1.8 indicates a high risk.

Looking at the Altman's Z-score for Halyk Bank over the past five years, we can see that the Z-score has consistently been above the 2.6 threshold, which suggests that the bank has been at a relatively low risk of bankruptcy over this time period.

In 2018, the Z-score was 2.286, which is relatively low, but still above the 1.8 threshold for high risk. This may indicate that the bank was in a relatively weak financial position at that time, but not at immediate risk of bankruptcy.

In 2019, the Z-score increased to 2.879, which is a positive sign, indicating that the bank's financial position had improved compared to the previous year.

In 2020, the Z-score decreased slightly to 2.773, which could be due to changes in the company's financial performance or external factors such as the COVID-19 pandemic and its impact on the economy.

In 2021, the Z-score increased slightly to 2.829, indicating a slight improvement in the bank's financial position compared to the previous year.

In 2022, the Z-score increased further to 3.130, suggesting that the bank is in a relatively strong financial position and at low risk of bankruptcy.

Table 2 – "CAMELS Approach"

CAMELS approach					
	2022	2021	2020	2019	2018
Capital Adequacy	0.185481341	0.1990043	0.255408997	0.2193962	0.200234202
Asset Quality		5.17 %	7.77 %	11.26 %	18.18 %
Management	0.317455	0.317506	0.333598	0.356575	0.363670
Earnings: Return on Assets (ROA)	3.87 %	3.82 %	3.39 %	3.62 %	2.83 %
Liquidity	0.691334544	0.6152119	0.573217052	0.5590336	0.519928057
Created by the author based on the own calculations.					

Capital Adequacy (C): The bank's capital adequacy ratio has increased from 0.2 in 2018 to 0.1855 in 2022, which indicates that the bank's capital position has improved over time. The capital adequacy ratio measures the bank's ability to absorb losses, and a higher ratio indicates a stronger capital position.

Asset Quality (A): The bank's asset quality has improved over the years, as reflected by the declining non-performing loan ratio (NPL). The NPL ratio has decreased from 18.18 % in 2018 to 5.17 % in 2021. A lower NPL ratio indicates that the bank has a lower proportion of bad loans in its portfolio, which is positive for its financial health.

Management (M): The bank's management rating has remained relatively stable over the years, with a slight decline in 2021 and 2022. The management rating takes into account the bank's leadership, risk management, and overall corporate governance. While the decline in the rating may be a cause for concern, the bank's rating remains in the satisfactory range.

Earnings (E): The bank's earnings have been relatively stable over the years, with a slight increase in 2022. The bank's return on assets (ROA) has remained in the range of 2.83 % to 3.87 %, which is a positive sign for its financial performance. A higher ROA indicates that the bank is generating more profits relative to its assets.

Liquidity (L): The bank's liquidity position has been improving over the years, as

reflected by the increasing liquidity ratio. The liquidity ratio has increased from 0.5199 in 2018 to 0.69133 in 2022, which indicates that the bank has more liquid assets to meet its short-term obligations. A higher liquidity ratio is positive for a bank's financial health.

While the CAMELs approach and Altman Z-score are widely used and validated methods for assessing credit risk, they also have some drawbacks and limitations:

Limited scope: The CAMELs approach and Altman Z-score are based solely on financial data and do not consider other factors that may impact credit risks, such as market conditions, competitive factors, or management quality.

Historical data: The CAMELs approach and Altman Z-score are based on historical financial data, which may not be a good predictor of future credit risk. Financial conditions and market dynamics can change rapidly, and historical data may not reflect these changes.

Generalization: The CAMELs approach and Altman Z-score are generalized methods that do not account for the specific characteristics and circumstances of individual borrowers. This can lead to inaccurate assessments of credit risk for certain borrowers.

Limited transparency: The CAMELs approach and Altman Z-score are complex models that can be difficult to understand and interpret for non-experts. This can limit the transparency of credit risk assessments and make it difficult for borrowers to understand how their credit risk is being evaluated.

Model assumptions: Both the CAMELs approach and Altman Z-score are based on certain assumptions about the underlying data and statistical relationships. If these assumptions are not met, the models may not accurately predict credit risk.

To address the drawbacks of the CAMELs approach and Altman Z-score, a possible new approach that could be created would be to combine the strengths of these methods with other techniques that can account for non-financial factors and provide more granular and personalized assessments of credit risk.

One possible approach would be to use machine learning algorithms to analyze both financial and non-financial data sources, such as customer feedback or social media sentiment, in order to identify patterns and correlations that are predictive of credit risk. By incorporating a wider range of data sources, this approach could potentially provide more accurate and personalized assessments of credit risk, while also accounting for non-financial factors that may impact credit risk.

Another possible approach would be to use predictive analytics techniques to identify early warning signals of credit risk, such as changes in financial ratios or market conditions, in order to enable more timely and proactive risk management. By identifying potential credit risk issues before they become critical, this approach could help reduce the likelihood of default and improve overall credit quality.

The present study proposes the implementation of predictive analytics methodologies to address the research problem. To this end, the R-studio software will be employed as a tool to conduct the analysis.

It is known that most banks earn their money by using customer deposits to create a credit for borrowers, but as credit transactions and loans increase, the risk associated

with them also increases. This can lead to poor management of the bank's balance sheet, cause a decrease in profits and liquidity, and damage the bank's reputation. Many scientists have studied the impact of credit risk on the performance of banks, and this study is aimed at studying this impact on commercial banks in Kazakhstan using the R-studio. It aims to answer whether credit risk affects profitability and whether there is a correlation between profitability and credit risk.

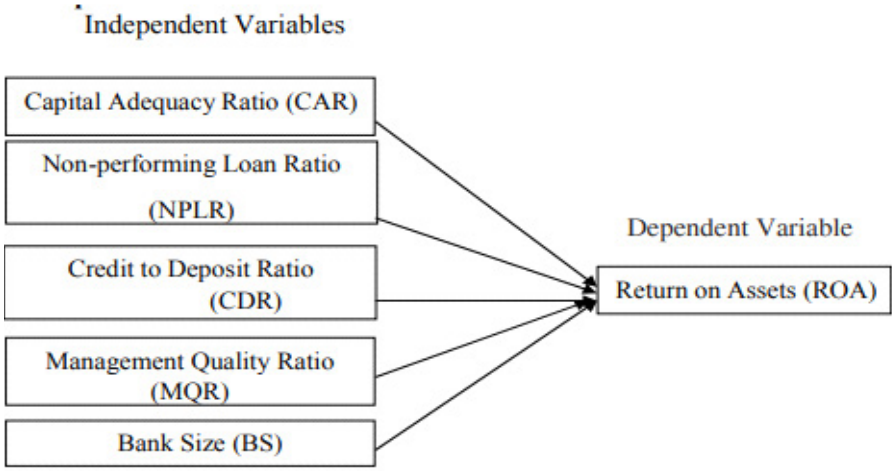

Figure 1 – "Conceptual Framework for the Study."
Source: based on the article "The Impact of Credit risk management on the Financial performance of Nepalese Commercial Banks" [4]

This model aims to investigate how credit risk impacts the performance of commercial banks in Kazakhstan between 2018–2022. The selected timeframe incorporates the most recent data and includes a combination of cross-sectional and time series data, making it suitable for analysis. The research design used in this study is descriptive and causal-comparative.

The convenience sampling method was used in choosing the banks for the study. The present analysis focuses on four second-tier banks operating in Kazakhstan, namely Halyk Bank, Forte Bank, Kaspi Bank, and CenterCredit Bank. These institutions have been selected based on their stable forecast rating of Ba2 – B1 as determined by Moody's. Additionally, they hold a prominent position as part of the top five banks operating within the Kazakhstani market.

The information utilized in this study was obtained from the annual reports of the selected banks. This information encompasses both time-series and cross-sectional data, resulting in a pooled dataset used to analyze the impact of credit risk on commercial bank performance. The analysis was conducted using pooled data regression, and the R-studio software was utilized for data processing and analysis.

Study variable and hypothesis

The variables under examination in this study consist of both dependent and

independent variables. The identification and classification of these variables are critical in facilitating an accurate and comprehensive analysis.

Dependent variable. It is important to acknowledge that there exists a range of metrics that can be employed to gauge bank performance. The specific performance measure employed in this study is dependent on the research objectives. Accordingly, the return on assets (ROA) has been selected as the dependent variable in this analysis to signify bank performance.

Independent variable.

Capital Adequacy Ratio. This variable is an independent factor utilized to assess bank performance and is widely regarded as a fundamental metric of a bank's financial robustness from the perspective of regulatory bodies.

H_0: The CAR has no effect on bank performance.

$H_{alternative}$: The capital adequacy ratio exerts a noteworthy and favourable impact on bank performance.

Asset Quality. The indicators of asset quality utilized in this study centre around the non-performing loans ratio (NPLs), which serves as a proxy for asset quality. Additionally, the allowance or provision for loan loss reserves is also considered.

H_0: NPLR has no effect on bank performance.

$H_{alternative}$: Non-performing loan ratio exerts a noteworthy and adverse impact on bank performance.

Liquidity. The CDR is a vital instrument for assessing a bank's liquidity position, as it measures the percentage of deposits allocated to credit utilization. A greater CDR signifies greater proficiency in the bank's deployment of acquired funds.

H_0: The CDR has no effect on bank performance.

$H_{alternative}$: Credit to deposit ratio exerts a noteworthy and adverse impact on bank performance.

Management quality ratio. Management soundness is a subjective variable that reflects the extent to which the board of directors exercises effective control over a bank's resources in order to safeguard the interests of its shareholders. This metric is typically calculated by dividing a bank's total operating income by its total assets and is considered a qualitative measure of management effectiveness.

H_0: The MQR has no effect on bank performance.

$H_{alternative}$: Management quality ratio exerts a noteworthy and favourable impact on bank performance.

Bank size. In assessing the performance of the banking system, one of the variables used for control purposes is the size of the bank, which is typically measured by its total assets. This is a widespread practice in academic research on the subject.

H_0: The BS has no effect on bank performance.

$H_{alternative}$: Bank size exerts a noteworthy and favourable impact on bank performance.

The variables chosen for the study have been presented in the Table along with their definitions, methods of measurement, and expected signs based on prior research.

The expected sign refers to a statistical approach used to demonstrate the correlation between two variables. A positive expected sign indicates that when one variable

increases, the other variable also increases, while a negative expected sign suggests that when one variable increases, the other variable decreases.

Table 3 – "Variables definition, measurement and expected sign."

No.	Abbreviation variables	Descriptions	Measurement	Expected sign
1	ROA	Return on Assets	Net Profit to Total Assets	NA
2	NPLR	Non-performing loan ratio	NPL to Gross loans and advances	-
3	CAR	Capital adequacy ratio	Capital to Risk-weighted Assets	+
4	CDR	Credit to Deposit ratio	Total loans to Total Deposits	-
5	MQR	Management quality ratio	Total Operating Income to Total Assets	+
6	BS	Bank size	Natural logarithm of total assets	+
Source: based on the article "The Impact of Credit risk management on the Financial performance of Nepalese Commercial Banks" [4]				

Results and Discussion

Descriptive statistics

Table 5 presents a summary of the descriptive statistics for all variables utilized in the study. The primary financial performance indicator examined in the analysis is the return on assets (ROA), and five credit risk indicators are considered: the capital adequacy ratio (CAR), non-performing loan ratio (NPLR), management quality measured by the total operating income to total assets (MQR), credit to deposit ratio (CDR), and bank size (BS). The results indicate that the average value of the bank's performance is reported.

Steps with codes in R-studio

The following code reads and outputs a table from Excel to R-studio.

```
Library (readxl)
DA <- read_excel ("new r.xlsx")
View (DA)
```

Table 4 – "Pooled data of ratios."

ROA	CAR	NPLR	CDR	MQR	BS
2.83 %	20.02 %	15.38 %	0.5333	0.0748	16.0082
3.62 %	21.94 %	10.12 %	0.5857	0.0739	16.0385
3.39 %	25.54 %	7.21 %	0.5963	0.0696	16.1561
3.82 %	19.90 %	4.91 %	0.693	0.0737	16.308
3.87 %	18.55 %	5.10 %	0.7493	0.0864	16.4766
1.72 %	17.86 %	4.60 %	64.12 %	6.37 %	14.33948
2.04 %	18.30 %	5.30 %	58.72 %	6.29 %	14.54304
2.53 %	22.25 %	6 %	0.540484	7 %	14.55232
2.64 %	24.31 %	7.16 %	46.66 %	6.77 %	14.70167
3.52 %	20.22 %	4.90 %	58.33 %	8.28 %	14.84133
6.54 %	23.00 %	8.90 %	0.865427	0.079567	14.34593
9.01 %	22.40 %	9.00 %	0.794177	0.109317	14.59831
9.38 %	18.80 %	9 %	0.653104	0.113236	14.84753
12.06 %	18.00 %	4.70 %	0.879732	0.146567	15.09864
11.50 %	18.00 %	5.90 %	0.788566	0.140692	15.44899

0.60 %	17.10 %	15.50 %	0.901496	0.028195	14.23275
0.14 %	17.40 %	12.6 %	1.024449	0.028155	14.19425
0.67 %	19.10 %	11 %	0.848822	0.029531	14.43461
0.99 %	19.80 %	7.70 %	0.841172	0.032734	14.54754
Created by the author using R-studio					

Regression Analysis

The following code outputs regression coefficients (intercept) for all ratios.

mod<- lm(DA$ROA~DA$CAR+ DA$NPLR+ DA$CDR+ DA$MQR+ DA$BS)

mod

```
Call:
lm(formula = DA$ROA ~ DA$CAR + DA$NPLR + DA$CDR + DA$MQR + DA$BS)

Coefficients:
(Intercept)       DA$CAR      DA$NPLR       DA$CDR       DA$MQR
   -0.07002      0.17152      0.08850      0.05932      1.12211
      DA$BS
   -0.00375
```

Figure 2 – "Regression coefficients"
Source: Results are drawn from R-studio

This code is used to perform variance analysis (ANOVA) of the linear regression model and display the results on the screen.

anova(mod)

```
Analysis of Variance Table

Response: DA$ROA
           Df    Sum Sq   Mean Sq  F value    Pr(>F)
DA$CAR      1 0.0000000 0.0000000   0.0001 0.9917389
DA$NPLR     1 0.0025382 0.0025382  51.9919 6.841e-06 ***
DA$CDR      1 0.0011384 0.0011384  23.3193 0.0003293 ***
DA$MQR      1 0.0197962 0.0197962 405.4949 3.485e-11 ***
DA$BS       1 0.0001211 0.0001211   2.4800 0.1393171
Residuals 13 0.0006347 0.0000488
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figure 3 – "Analysis of Variance Table."
Source: Results are drawn from R-studio

The next code is used to display a detailed summary of the results of the linear regression model on the screen.

summary(mod)

```
Call:
lm(formula = DA$ROA ~ DA$CAR + DA$NPLR + DA$CDR + DA$MQR + DA$BS)

Residuals:
      Min        1Q    Median        3Q       Max
-0.008705 -0.004801  0.000855  0.002830  0.013843
```

```
Residuals:
      Min        1Q    Median        3Q       Max
-0.008705 -0.004801  0.000855  0.002830  0.013843

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.070025   0.042313  -1.655 0.121872
DA$CAR       0.171524   0.077565   2.211 0.045538 *
DA$NPLR      0.088497   0.055758   1.587 0.136491
DA$CDR       0.059325   0.013247   4.478 0.000622 ***
DA$MQR       1.122113   0.057007  19.684 4.64e-11 ***
DA$BS       -0.003750   0.002382  -1.575 0.139317
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.006987 on 13 degrees of freedom
Multiple R-squared:  0.9738,    Adjusted R-squared:  0.9637
F-statistic: 96.66 on 5 and 13 DF,  p-value: 8.188e-10
```

Figure 4 – “Summary of linear regression.”
Source: Results are drawn from R-studio

According to the data presented in Figure 8, the R-square value was found to be 0.9738. This indicates that approximately 97.38 percent of the variance observed in the value of ROA can be attributed to the influence of the independent variables under consideration. Additionally, the adjusted R-square value of 0.9637 suggests that, after adjusting for other factors, the independent variables collectively account for approximately 96.37 percent of the observed variation in the dependent variable ROA. These findings suggest a strong relationship between the independent and dependent variables in the study.

The study findings suggest that non-performing loans and the financial performance of commercial banks are negatively associated, albeit with a weak correlation to return on assets. Conversely, the results indicate a positive, yet weak, correlation between CDR and bank performance. In addition, the study reveals that the capital adequacy ratio has a positive and significant effect on the financial performance of commercial banks in Kazakhstan, thus supporting the hypothesis under investigation.

The study findings reveal that the management quality ratio has a positive and statistically significant impact on the financial performance of commercial banks, as evidenced by a significant positive correlation with return on assets. Specifically, an increase in total operating income corresponds to an improvement in bank performance. These findings support the hypothesis that the management efficiency ratio has a significant effect on the financial performance of commercial banks in Kazakhstan. In contrast, the study indicates a weak and negative relationship between bank size and financial performance (ROA), with no significant correlation observed.

Correlation Analysis

This code is used to calculate the correlation matrix between the selected data columns.

```
x_col<-cor(DA[,c(2,3,4,5,6)])
view(x_col)
```

Table 5 – "Correlation matrix table."

	CAR	NPLR	CDR	MQR	BS
CAR	1.00000000	- 0.09065608	- 0.4912443	0.03004054	0.2055246
NPLR	-0.09065608	1.00000000	0.27674540	-0.45748685	- 0.1617064
CDR	-0.49124427	0.2767450	1.00000000	- 0.13114869	- 0.3482389
MQR	0.03004054	-0.45748685	- 0.1311487	1.00000000	0.3235710
BS	0.20552461	- 0.16170635	- 0.3482389	0.32357104	1.00000000
Created by the author using R-studio					

Table 6 displays the correlation matrix for the variables, which indicates that none of the correlation coefficients between the independent variables exceeds 0.7. This suggests that multicollinearity is not present among the independent variables. Therefore, there is no conclusive evidence of multicollinearity among the independent variables.

After executing the following commands, the *"car"* package will be installed and downloaded, and the functions from this package will be available for use.

install.packages ("car")

library (car)

In the R-studio vif(mod) is used to calculate the values of the Variance Inflation Factor (VIF) for each variable in the multiple regression model

Vif (mod)

Linear regression assumes the absence of multicollinearity in the data, which occurs when the independent variables exhibit a high correlation with each other. To test for multicollinearity, researchers may use the Variance Inflation Factor (VIF), where a VIF value of 10 or greater indicates significant multicollinearity. The VIF values provided in the table suggest that there is no evidence of multicollinearity in the statistical data being studied.

```
   DA$CAR   DA$NPLR    DA$CDR    DA$MQR     DA$BS
1.326247 1.354493 1.532758 1.389902 1.259557
```

Figure 5 – "Variance Inflation Factor"
Source: Results are drawn from R-studio

Table 6 – "Test For Multicollinearity"

Variable	VIF	1/VIF
CAR	1.3262	0.7540
NPLR	1.3545	0.7383
CDR	1.5328	0.6524
MQR	1.3899	0.7195
BS	1.2596	0.7939
Mean VIF	1.3727	
Created by the author using R-studio		

In the R studio, this code is used to test the hypothesis of homoscedasticity of residuals in a linear regression model given by the *mod* object. Using *lmtest: test(mod)* helps to assess the adequacy of the model and take appropriate measures.

install.packages ("lmtest")
library (lmtest)
lmtest: bgtest (mod)

```
        Breusch-Godfrey test for serial correlation of order up to 1

data:  mod
LM test = 2.4402, df = 1, p-value = 0.1183
```

Figure 6 – "Test for Heteroskedasticity"
Source: Results are drawn from R-studio

The Breusch-Pagan test is a statistical method that assesses the presence of heteroscedasticity in linear regression models. This test is constructed based on the Lagrange multiplier principle and evaluates the potential dependence of the error variance on the values of the explanatory variables. In essence, a significant result from this test indicates the absence of heteroscedasticity in the regression model under examination.

The foregoing analysis of profitability indicators suggests that the Management Quality Ratio exerts a significant impact. Accordingly, it can be inferred that the effective implementation of credit risk management practices has a direct and positive effect on the profitability of banks. Thus, a strong Management Quality Ratio is indicative of the effective implementation of credit risk management practices. Banks that have a better understanding of credit risk and are able to manage it effectively are more likely to generate higher profits. On the other hand, banks that fail to manage credit risk adequately may experience higher loan losses, which can erode profitability.

This problem is also present in the banks of Kazakhstan. Kazakhstan's commercial banks face various challenges in credit risk management that can affect their profitability and overall financial health. Some of the possible problems that commercial banks in Kazakhstan may encounter in credit risk management are:

Inadequate credit risk assessment

Banks may face challenges in properly assessing credit risk due to limited access to accurate and timely information about borrowers, weak credit analysis skills, and a lack of robust credit scoring models.

For instance, in many cases, banks in Kazakhstan may not have access to up-to-date credit information about borrowers, making it difficult to assess the creditworthiness of potential borrowers. This is particularly true for small and medium-sized enterprises (SMEs), which often lack a comprehensive credit history. As a result, banks may end up approving loans to borrowers who have a higher probability of default, increasing credit risk exposure.

Weak credit risk monitoring

Banks may struggle to effectively monitor borrowers' creditworthiness, which can result in delayed identification of credit risk deterioration and higher loan losses.

For example, banks in Kazakhstan may not have sufficient mechanisms to monitor borrowers' financial health and timely identify any signs of default. This may include

inadequate systems to track borrowers' repayment history or failure to conduct periodic credit reviews. As a result, banks may not be aware of changes in a borrower's financial situation, such as declining revenues or increasing debt, which can increase the probability of default.

Moreover, weak credit risk monitoring can also be due to a lack of trained staff and insufficient resources allocated to credit risk management. Banks may not have enough credit analysts or risk managers to effectively monitor borrowers' creditworthiness or may not provide them with the necessary tools and resources to carry out their duties.

Insufficient collateral valuation

Banks may face challenges in accurately valuing collateral, leading to overvaluation or undervaluation of collateral, and the risk of under-collateralization.

For example, banks in Kazakhstan may accept collateral in the form of real estate but may not have proper mechanisms to evaluate the true value of the property. This can lead to overvalued collateral and give borrowers an opportunity to obtain larger loans than they can repay, leading to potential loan defaults and losses for banks.

Inadequate risk diversification

This problem arises when banks have concentrated credit exposures in a single industry, geographic region, or borrower, leading to higher credit risk and potential losses.

For example, in Kazakhstan, banks may have concentrated credit exposures in the oil and gas sector, which accounts for a significant portion of the country's economy. This can lead to higher credit risk if there is a decline in the sector, leading to potential loan defaults and losses.

Insufficient credit risk management policies

Banks may lack comprehensive credit risk management policies and procedures, which can lead to inconsistencies in credit risk assessment and monitoring.

For example, banks in Kazakhstan may lack policies related to credit risk assessment, credit monitoring, and credit risk reporting. This can lead to inadequate credit risk evaluation and monitoring, leading to potential loan defaults and losses.

Based on foreign experience, here are some specific recommendations for improving the credit risk management system in commercial banks of Kazakhstan.

Develop a credit risk management framework based on international best practices.

For example, the United States has established the Federal Financial Institutions Examination Council (FFIEC) which provides guidance on credit risk management to banks and financial institutions. The Monetary Authority of Singapore (MAS) also provides guidance on credit risk management to banks in Singapore. These frameworks can be used as a reference to develop a comprehensive credit risk management framework in Kazakhstan.

Utilize credit scoring models and data analytics.

For example, in the United States, FICO scores are widely used to evaluate borrowers' creditworthiness. Studies have shown that the FICO score is highly predictive of future credit behavior, such as the likelihood of default, delinquency, or bankruptcy (FFIEC, 2020). For example, a study by the Consumer Financial Protection Bureau (CFPB)

found that the FICO score is highly predictive of future delinquency and default rates for auto loans, credit cards, and mortgages.

Enhance regulatory oversight.

For instance, in Singapore, the MAS conducts regular assessments of banks' credit risk management processes and imposes penalties for non-compliance (MAS, 2021). Kazakhstan's National Bank can adopt these practices to enhance regulatory oversight.

Train employees in credit risk management

For example, the Risk Management Association (RMA) (RMA, 2021). provides training and development programs for bankers in credit risk management in the United States. Kazakhstan's banks can adopt these practices to train their employees in credit risk management.

Artificial Intelligence.

AI models can use advanced statistical techniques and machine learning algorithms to assess creditworthiness, evaluate the probability of default, and predict potential losses. These models can continuously learn and improve over time, refining their assessments based on new data and feedback (Bao, 2021). Some foreign banks are already successfully using AI in credit risk management. For example, the American bank Wells Fargo uses machine learning to determine the risk of fraud, and the Chinese bank “Ping An” uses neural networks to predict credit risk (Hua, 2019). However, it is necessary to consider some risks associated with the use of AI, such as the need for high data accuracy, system reliability and data security (Zhang, 2018). In addition, it is necessary to ensure a balance between the use of AI and the human factor to maintain a humanitarian approach to credit risk management.

Conclusion

Credit risk management is an indispensable function within commercial banks, and it is imperative to leverage all available methods and technologies to mitigate risks and enhance the quality of the loan portfolio. The challenges identified in this study highlight the need for continuous improvement and innovation in credit risk management practices.

Moving forward, further research is recommended, particularly in the realm of utilizing artificial intelligence (AI) in credit risk management. Investigating specific methods and the most effective technologies applicable to commercial banks in Kazakhstan would be beneficial. AI has the potential to revolutionize credit risk management by improving data analysis, risk modeling, and decision-making processes. By harnessing the power of AI, commercial banks can gain valuable insights into borrower behavior, detect patterns, and identify early warning signals, thus enabling more accurate risk assessment and proactive risk mitigation strategies.

In conclusion, by embracing technological advancements, conducting further research on AI applications, and maintaining regulatory compliance, commercial banks in Kazakhstan can enhance their credit risk management practices, reduce potential losses, and foster a more stable and profitable lending environment. Continuous improvement and a proactive approach to risk management are essential for sustained success in the ever-evolving financial landscape.

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ХАЛЫҚАРАЛЫҚ АҚПАРАТТЫҚ ЖӘНЕ КОММУНИКАЦИЯЛЫҚ ТЕХНОЛОГИЯЛАР ЖУРНАЛЫ

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Мрзабаева Раушан Жалиевна

КОМПЬЮТЕРНАЯ ВЕРСТКА
Жадыранова Гульнур Даутбековна

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