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ASSESSMENT OF THE CREDIT PORTFOLIO RISK OF KAPITAL BANK OJSC

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ABSTRACT

This study provides the evolution of credit portfolio risk in the Azerbaijani banking sector, focusing on the case of Kapital Bank over the period 2020–2024. The expansion of lending activity and increased economic uncertainty, particularly during the post-pandemic recovery, have heightened the need for a comprehensive assessment of credit risk behaviour. The research addresses the problem of insufficient multi-dimensional analysis of how portfolio risk changes over time. The primary aim is to evaluate the structural dynamics of credit risk by examining both its magnitude and its distributional characteristics. Using quarterly data, the study applies statistical measures that capture average risk levels, variability, directional movements and distributional properties in order to analyse changes in portfolio stability. The findings reveal a gradual transition from high and volatile risk levels in the initial years to a more stable and balanced structure in 2023–2024. Overall, the results underscore the increasing effectiveness of risk-oriented lending practices and the strengthening of portfolio management across the analysed period.

1. INTRODUCTION

The expansion of the credit process and the redistribution of financial resources through banks have significantly increased the importance of the banking sector in modern economic systems (Freixas and Rochet, 2008). By performing the function of financial intermediation, banks ensure the financing of investments, support the expansion of entrepreneurial activities, and create conditions for efficient capital management in the economic circulation. In developing countries, this role is even more critical, as the credit provision to the real sector largely depends on the banking system (Demirgüç-Kunt and Maksimovic, 2002). Therefore, the stability of the banking sector, the monitoring of asset quality, and risk management are of strategic importance for macroeconomic stability.

Along with the expansion of the banking sector, the scale and complexity of risks have also increased. The volatility observed in financial cycles, instability in borrower behavior, and rapid growth in loans have made banks more vulnerable to risk (Laeven and Valencia, 2013). Particularly, credit risk is considered the most critical risk category for banks, as it directly

impacts the quality of bank assets. The probability of loan defaults increases financial losses, weakens liquidity positions, and exerts pressure on capital adequacy (Greenbaum and Thakor, 2007). Therefore, the proper measurement of credit risks has become one of the key priorities in modern banking management.

The period from 2020 to 2024 has been characterized by significant changes not only in the global economy but also in the Azerbaijani banking sector. The shock caused by the COVID-19 pandemic increased uncertainty in borrowers' repayment ability and created sharp changes in the risk structure of credit portfolios (World Bank, 2021). In the post-pandemic period, the gradual recovery of economic activity, the expansion of credit volumes, and the increased demand for consumer loans have elevated the volatility of credit portfolios. At the same time, restructuring programs, financial concessions, and changing macroeconomic conditions directly influenced the formation of portfolio risks (OECD, 2022).

For a systemically important bank like Kapital Bank OJSC, the analysis of the risk level of the credit portfolio is of particular relevance. The bank's large-scale portfolio, broad customer base, and multifaceted credit structure necessitate the analysis of both upward and downward risks. Empirical analysis based on quarterly indicators allows the determination of the trajectory of the risk level over time and provides a more accurate assessment of changes in the portfolio structure.

The primary goal of this study is the empirical assessment of the risk level of Kapital Bank OJSC's credit portfolio for the period from 2020 to 2024 using multidimensional statistical approaches. The research envisages measuring credit risk not only through traditional indicators but also through indicators reflecting the portfolio's volatility, asymmetry, and distribution characteristics. To this end, the study analyzes changes in the risk structure of the credit portfolio based on the share of non-performing loans (NPL), portfolio dispersion, standard deviation, and semi-variance indicators that better capture downside and upside movements in risk (PSV and NSV), as well as skewness and kurtosis coefficients that determine the shape of the distribution.

The aim of the study is not limited to quantitatively determining the risk level but also includes revealing the time trajectory of the risk dynamics of the credit portfolio, clarifying the structural characteristics of the risk distribution, and identifying the factors affecting changes in portfolio risk at different stages. This approach allows for a comprehensive assessment of credit risk from content, form, and behavior aspects, and forms an analytical basis for improving Kapital Bank's risk management strategy.

Based on these objectives, the study is systematically structured around the following research questions and their corresponding hypotheses.

Research Question 1:

How has the overall level of credit portfolio risk at Kapital Bank OJSC evolved over the period 2020–2024?

Hypothesis 1:

During the analyzed period, the level of credit portfolio risk exhibited differentiated behavior across distinct phases.

Research Question 2:

How have risk variability and downside risk components within the credit portfolio evolved over time?

Hypothesis 2:

Risk variability and downside risk components within the credit portfolio were formed with unequal intensity across different periods.

Research Question 3:

What differences emerged between the pandemic and post-pandemic phases in terms of the distributional form and structural characteristics of credit portfolio risk?

Hypothesis 3:

While the distribution of credit portfolio risk during the pandemic phase was more asymmetric and pronounced, the post-pandemic period exhibited a more balanced risk structure.

2. LITERATURE REVIEW

The assessment of credit portfolio risks has been at the center of international scientific discussions for many years as one of the main directions of modern banking regulations, financial stability policies, and risk management frameworks. The analysis of credit portfolio risk was first systematized through Markowitz's (1952) portfolio selection theory, which established the principle of risk measurement based on the dispersion of asset returns and covariance. The Markowitz model demonstrated the possibility of reducing risk through diversification, and this concept was later applied to bank assets, particularly credit portfolios (Jorion, 2007; Saunders and Allen, 2002). This approach has provided a theoretical foundation for analyzing the quality of bank assets and the risk-return ratio.

The structural modeling of credit risk was introduced by Merton (1974), who proposed determining the probability of default based on the ratio of the market value of a firm's assets to its debt obligations. Vasicek (2002) extended this model to the context of multiple borrowers and developed the Asymptotic Single Risk Factor (ASRF) model. This approach enabled the linking of unexpected losses in bank portfolios to capital requirements. The Basel Committee's (BCBS, 2011) framework documents have served as the primary foundation for the international regulation of credit risk. In these documents, the calculation of expected losses has been standardized with the application of components such as default probability (PD) and exposure at default (EAD), and the relationship between risk and capital adequacy has been made more transparent.

However, many studies have shown that the distribution of credit risks often deviates from normal behavior. Inequality in the distribution and the occurrence of rare but large values more frequently indicate that classical dispersion-based models do not fully capture the risks. As a result, modern research increasingly utilizes non-linear methodologies based on indicators such as semi-variance, skewness, and excess to assess credit risk (Harvey and Siddique, 2000). These indicators provide a more accurate reflection of the distribution form of risks in credit portfolios and help determine the direction of risk (Jobst, 2007).

Two main directions have emerged internationally for the assessment of credit portfolio risks: structural models (Merton, Vasicek, and their multi-period variations) and actuarial-type models

(CreditMetrics, CreditRisk+). The CreditRisk+ model (Credit Suisse, 1997; Han and Kang, 2008) models credit risk using the Poisson distribution and is based on the probability structure of default events. This model allows for the determination of the distribution of expected and unexpected losses in a credit portfolio (Crouhy, Galai and Mark, 2000). The ASRF approach, derived from the Vasicek model, has enabled the measurement of the overall risk level of a bank's portfolio by considering systematic risk factors. Gordy and Marrone (2012) introduced adjustments that account for portfolio granularity, which have become an important methodological basis for the formal assessment of concentration risk in Basel's credit risk framework.

Empirical studies show that the risks of credit portfolios are shaped interactively by bank-specific indicators, borrower behavior, and macroeconomic volatility. Demirgüç-Kunt and Detragiache (1998) demonstrated that one of the main causes of banking crises is the pro-cyclical movement of credit risks with economic cycles. Reinhart and Rogoff (2009) emphasized the long-term historical relationship between credit expansion and financial stability, showing that systemic crises occur when risks are not managed properly.

Studies conducted in regional and transition economies, particularly in Central and Eastern Europe (Kanapickienė et al., 2022; Şahin and Acar, 2024; Dietsch and Petey,2011) indicate that macroeconomic volatility, interest rates, and sector concentration have a significant impact on the structure of credit portfolio risks. Research conducted in Azerbaijan also follows international trends. Hasanov and Huseynov (2013) evaluated the impact of bank credits on economic growth and noted the crucial role of credit expansion in the development of the non-oil sector. Mukhtarov, Yuksel, and Mammadov (2018) empirically identified the factors forming credit risks in Azerbaijan's commercial banks, such as portfolio sector structure, macroeconomic volatility, and management effectiveness.

In recent years, new approaches to modeling credit risks have emerged in local research. Muqumova (2025) empirically analyzed the evaluation of credit risks in commercial banks and identified stabilization trends in the dynamics of risk indicators in the post-pandemic period. This approach emphasizes the importance of applying mathematical and statistical models in assessing credit risks.

The Financial Stability Reports of the Central Bank of Azerbaijan (2021–2024) reflect the changes in the structure of the credit portfolio in detail. These reports highlight the expansion of consumer loans, the variability of collateral rates across sectors, and the reduction of NPL levels as key factors influencing the dynamics of risks. The application of IFRS 9 standards has improved the risk reporting and capital adequacy control mechanisms in banks (CBAR, 2023).

Results from international organizations, particularly the BIS (2022) and IMF (2023) reports, also show that in developing economies, the level of credit portfolio risks is closely linked to the share of consumer loans, exchange rate volatility, and sector concentration. These trends are also evident in the Azerbaijani context. Both international models (Markowitz, Merton, Vasicek, CreditRisk+, Gordy), and local empirical results (Hasanov and Huseynov, 2013; Mukhtarov et al., 2018; Muqumova, 2025; CBAR, 2024) form a reliable theoretical and methodological basis for the assessment of credit portfolio risks. A general analysis of the literature suggests that in modern banking systems, the assessment of credit portfolio risks should be based on the joint application of structural model approaches and statistical indicators. This framework defines the scientific foundations for the empirical analysis conducted for Kapital Bank for the period 2020–2024 and ensures the methodological robustness of the study.

3. AIM OF THE STUDY AND THE METHODOLOGY

In this study, the credit portfolio risks of Kapital Bank OJSC for the period 2020–2024 were assessed using a multidimensional statistical approach. The credit portfolio, as one of the key structural elements of the banking system in terms of profitability and stability, is also a major source of potential losses. Therefore, the precise measurement of risks and the determination of their distribution characteristics across the portfolio are of significant importance for the bank's strategic management.

The data used in the study were taken from Kapital Bank's quarterly financial reports for 2020–2024 and the Financial Stability Reports of the Central Bank of the Republic of Azerbaijan. The selected period covers the post-pandemic recovery phase and the structural growth of consumer loans, making it a period with high-risk intensity and portfolio heterogeneity.

The quantitative assessment of financial risks began with Markowitz's (1952) portfolio variance theory. According to this approach, the total risk of a portfolio is determined not only by the individual risks of the individual assets but also by their interactions—i.e., covariance. This framework was later developed by researchers like Vasicek (2002) and Gordy (2003), leading to its widespread application in the calculation of capital requirements for bank credit portfolios and in risk regulation models.

Despite the theoretical advantages of the Markowitz model, it has one significant limitation: the assessment of risk is based on the concept of symmetric volatility and assumes that income-loss distributions follow a normal distribution. In reality, credit portfolios are often characterized by asymmetric and, at times, sharply negatively skewed distributions. For this reason, modern empirical studies also use indicators such as semi-variance, asymmetry, and kurtosis, alongside variance, to provide a more objective assessment of portfolio risk. To overcome this limitation, the semi-variance approach proposed by Sortino (1980) was applied in this research. In the semi-variance model, only negative directional changes (losses) are considered, meaning the actual impact of risk is assessed asymmetrically. This is a more suitable approach for bank credit portfolios, as the loss side is the primary source for strategic decisions within the bank.

The methodology is also enriched with the conditional asymmetry model developed by Harvey and Siddique (2000). This model is used to evaluate how credit risk is distributed and how sensitive the portfolio is to rare but large losses (tail risk). Asymmetry and kurtosis indicators allow for the measurement of the structure and non-normal nature of the risk distribution.

From a methodological perspective, the calculation of risk indicators was carried out through a multi-step system. In the initial phase, the total risk exposure of the portfolio was determined as follows:

$$S_p = \sum_{i=1}^{n} S_i \, p_i(c) \qquad (1)$$

In this study, S_i- denotes the share of the i-th loan in the portfolio, while, $p_i(c)$ represents the corresponding risk indicator of that loan. This formula is a simplified version of the compact portfolio risk assessment function proposed by Bessis (2015).

The average risk level of the portfolio is defined as follows:

$$L = \frac{S_p}{\sum_{i=1}^{n} S_i} \qquad (2)$$

This coefficient is based on Markowitz's (1952) variance model and characterizes the overall distribution of risk within the portfolio. A higher value of L indicates that higher-risk assets dominate the portfolio.

To determine the degree of risk volatility, the variance indicator was used:

$$V_p = \frac{\sum_{i=1}^{n} (p_i(c) - L)^2 \, S_i}{\sum_{i=1}^{n} S} \qquad (3)$$

Variance reflects the extent to which portfolio risk deviates from its average level and was proposed by Elton and Gruber (1995) as a primary measure of portfolio variability.

The square root of variance, the standard deviation, represents the overall level of volatility in the portfolio:

$$\sigma_p = \sqrt{V_p} \qquad (4)$$

This measure has been used by Crouhy, Galai and Mark (2000) to evaluate the stability of portfolio risks.

To assess the directional distribution of risk, semi-variance indicators were calculated (Sortino and Price, 1994):

$$PSV = \sum_{i=1}^{n} (t)^2 \, \frac{S_i}{S} \qquad (5)$$

$$NSV = \sum_{i=1}^{n} (l)^2 \, \frac{S_i}{S} \qquad (6)$$

Here, PSV measures upward (positive) deviations, while NSV measures downward (negative) deviations. A higher NSV indicates that the portfolio is more sensitive to downside risks.

To evaluate the amplitude of directional changes in risk, the square roots of semi-variances were calculated. This approach is recognized in the literature as semi-standard deviation, an extended form of the Sortino measure, and is used to quantify volatility only in a specific direction (Sortino and Price, 1994; Estrada, 2007).

$$psv = \sqrt{PSV} \qquad (7)$$

$$nsv = \sqrt{NSV} \qquad (8)$$

These indicators make it possible to comparatively assess the distribution of risks across upward and downward directions.

To determine the shape of the risk distribution, the skewness coefficient was applied:

$$S_k = \sum_{i=1}^{n} \frac{S_i}{\sum_{i=1}^{n} S_i} \frac{(p_i(c) - L)^3}{\sigma_p^3} \qquad (9)$$

Skewness indicates the direction of the distribution and which side of the portfolio the risk is concentrated on. If S_k<0, the distribution is negatively skewed, S_k>0 it indicates a distribution skewed toward positive returns.

In the final stage, kurtosis was used to determine the shape of the distribution and the probability of extreme events. Statistically, kurtosis measures the degree of "peakedness" at the center of the distribution and the intensity of values observed in the tails.

$$K = \sum_{i=1}^{n} \frac{S_i}{\sum_{i=1}^{n} S_i} \frac{(p_i(c) - L)^4}{\sigma_p^4} \qquad (10)$$

If the kurtosis value exceeds 3 (K>3), it indicates that observations are more concentrated around the mean but extreme values occur more frequently. Such a distribution suggests that despite the apparent stability of the portfolio, it is exposed to high-magnitude loss risks. Conversely, when K<3 the distribution is flatter, indicating a more balanced risk structure.

This methodological framework enables a multidimensional evaluation of the credit portfolio's risk structure. Variance and standard deviation measure the magnitude of risk, while semi-variance and skewness indicators assess its directional behavior. Thus, Markowitz's (1952) variance theory, Sortino's (1980) asymmetric risk concept, and the Harvey and Siddique (2000) conditional distribution model are synthesized within a single system to provide a scientific and statistical assessment of Kapital Bank's credit portfolio risks for the period 2020–2024.

4. EMPIRICAL RESULTS

In the context of this study, calculations based on the credit portfolio data of Kapital Bank OJSC for the period 2020–2024 have demonstrated how the risk level of the credit portfolio and its structural indicators have changed over the five-year period. The analysis is based on quarterly credit portfolio volumes (S_t) and non-performing loans (NPL_t) Using this data, quarterly risk shares were determined, and subsequently, indicators such as average risk level, variance, semi-variances, standard deviation, skewness, and excess were calculated.

Table 1 presents the final results of all these indicators over the five-year period. The indicators in the table were derived from initial quarterly data, where the share of non-performing loans in the portfolio for each quarter was taken as a risk indicator, the values were weighted by the overall size of the portfolio, and by calculating the square of the quarterly deviations, risk variance and standard deviation were obtained. Additionally, positive and negative semi-variances were calculated by separating the upward and downward deviations. Skewness and excess indicators, based on standardized deviations, were also obtained to evaluate the shape characteristics of the risk distribution.

Table 1. Risk Indicators of the Credit Portfolio (2020–2024)

Year	L (%)	V_p (%)	σ_p (%)	PSV (%)	NSV (%)	psv (%)	nsv (%)	S	K
2020	3.17	0.00474	0.688	0.00228	0.00245	0.478	0.495	-0.064	1.053
2021	3.18	0.00074	0.272	0.00038	0.00036	0.194	0.190	0.067	1.870
2022	2.33	0.00286	0.535	0.0008	0.00206	0.283	0.454	-1.015	2.185
2023	1.43	0.00004	0.066	0.00002	0.00002	0.045	0.048	-0.024	1.965
2024	1.85	0.00024	0.153	0.00006	0.00017	0.079	0.131	-1.142	2.534

The results show that for 2020, calculations confirmed that the average risk level of the credit portfolio was 3.17%, with noticeable variability in the risk indicators across the quarters. This variability is reflected in the high values of variance (0.004735%) and standard deviation (0.688%). The fact that the negative semi-variance exceeded the positive semi-variance indicates that the risk is concentrated more in downward deviations, showing that the portfolio is more sensitive to negative changes. The negative skewness value of (–0.064) indicates a slightly left-skewed distribution. These results show that in 2020, credit risks were formed in an unstable and volatile environment.

In 2021, the average risk level remained at 3.18%, the same as the previous year. The decrease in standard deviation to 0.272% indicates a transition to a more stable risk structure. The minimal difference between PSV and NSV values suggests that the risk is evenly distributed in both

upward and downward directions. The positive skewness (0.067) indicates a slight rightward skew in the distribution. These results confirm that credit risks were forming in a more regulated and manageable environment in 2021.

In 2022, the average risk level decreased to 2.33%, but the increase in standard deviation to 0.535% indicates greater variability in the risk distribution. The significantly higher negative semi-variance compared to positive semi-variance indicates that the risk is primarily concentrated in downward deviations. The skewness of –1.015 indicates a significant leftward skew in the risk distribution. The excess value below 3 indicates that the distribution has a flatter and more centralized structure.

2023 exhibited the most stable risk indicators over the five-year period. The average risk level dropped to 1.43%, and the standard deviation reached a very low value of 0.066%, indicating minimal volatility in risk formation. The near equality of PSV and NSV values demonstrates a balanced distribution of risk in both directions. The skewness of –0.024 suggests that the risk distribution is close to normal.

In 2024, the average risk level rose to 1.85%, and the increase in standard deviation (0.153%) indicates that some variability in risk had returned. The fact that NSV was higher than PSV indicates that the risk was more concentrated in the downward direction. The negative skewness value of (–1.142) suggests a strong leftward skew in the distribution. The high excess value indicates that deviations from the center of the distribution are more frequent.

These findings provide a comprehensive picture of how credit portfolio risks in Kapital Bank evolved between 2020 and 2024, with fluctuations in risk levels and distributions that reflect the economic conditions and changes in the banking environment during this period.

5. ANALYSIS OF EMPIRICAL RESULTS

The empirical assessment based on the credit portfolio risk indicators of Kapital Bank OJSC for the period 2020–2024 reflects the main trends and stability dynamics observed in the bank's risk structure. The calculations show that the average risk level (L) of the portfolio remained at 3.1% during 2020–2021, demonstrated a decreasing trend starting from 2022, and stabilized in the range of 1.4–1.8% during the 2023–2024 period. This decrease can be attributed to the widespread application of a risk-based approach in the bank's credit policy, portfolio restructuring, and the transition to a special management framework for non-performing assets.

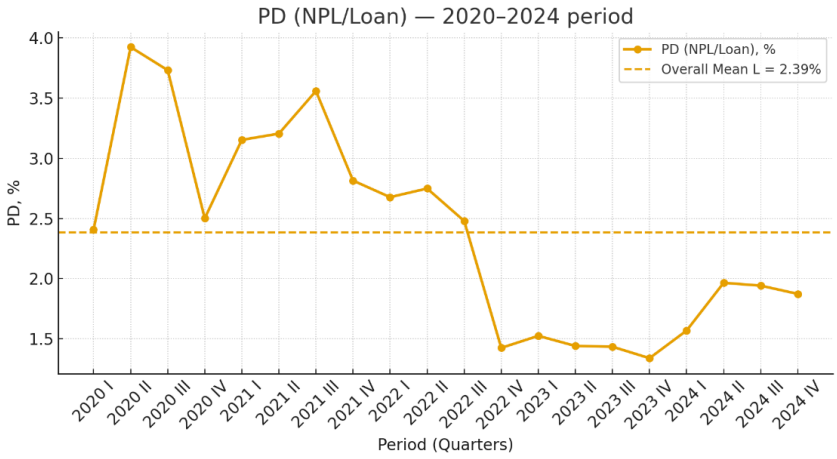

Fig. 1 PD and the average risk level of Kapital Bank's Credit Portfolio

Figure 1 depicts the actual risk indicator of Kapital Bank's credit portfolio – PD and the annual average risk value (L). As shown in the graph, the risk level was above average in 2020 and 2022, reflecting the impacts of the pandemic and macroeconomic instability. In 2023–2024, the PD indicators approached the annual average values, which resulted in a reduction in risks to a manageable level and an increase in the bank's portfolio stability.

The variance (V_p) and standard deviation (σ_p) indicators for the credit portfolio allow for the evaluation of risk variability. In 2020 and 2022, these indicators were relatively high, indicating an unstable distribution of risks. However, starting in 2023, the decrease in standard deviation suggests that the bank's portfolio structure has become more predictable and resilient. The reduction in risk variability can be linked to the deepening of the IFRS 9 methodology for calculating expected credit losses (ECL), as well as the improvement of internal credit scoring systems and PD–LGD models.

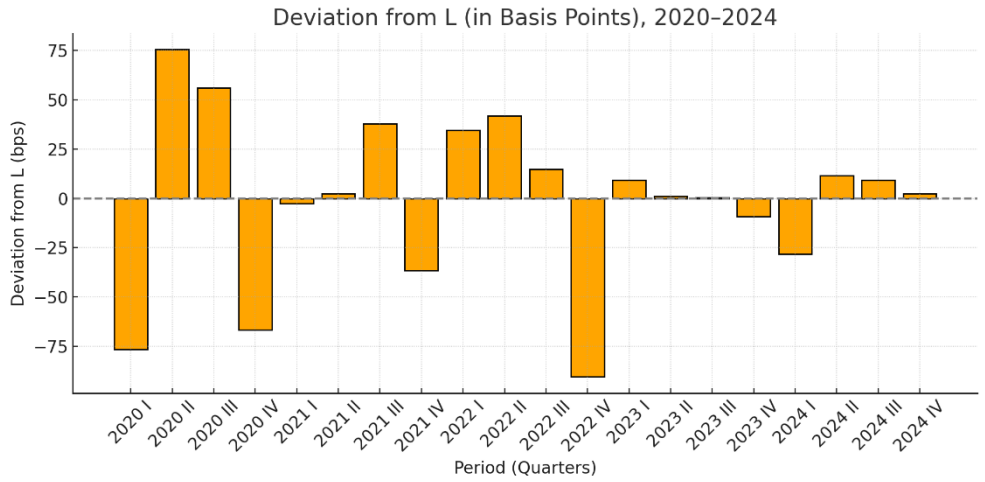

Fig. 2 Deviation from the average risk level of the credit portfolio (in basis points)

Figure 2 presents the deviations from L in basis points (bps), a unit of measurement used to express small changes in interest rates or risk indicators. This graph reflects the positive and negative deviations of the credit portfolio from the annual average risk level (L) on a quarterly basis. In 2020 and 2022, deviations ranged between ±70–80 bps, indicating the heterogeneous nature of the risks. In 2023–2024, the deviations were limited to ±20 bps, confirming that risks have become more concentrated and the portfolio has homogenized. This is directly related to the strengthening of the bank's risk management mechanisms, credit monitoring, and the automation of analysis systems.

The skewness (S_k) and kurtosis (K) indicators for the credit portfolio characterize the distribution form of the risks. In 2020–2021, the distribution was symmetric (Sk ≈ 0), while in 2022 and 2024, negative skewness indicates that risks were more concentrated on the "bad" side – i.e., segments with high loss risks. This could be due to the impact of high interest rates in the consumer credit segment and macroeconomic volatility. The increase in the kurtosis coefficient in the 2022–2024 period indicates that extreme risk events have become more frequent, reflecting the presence of customer groups with differing risk profiles.

Evaluations based on the positive and negative semi-variance indicators (PSV and NSV) show that in 2020–2021, risks were evenly distributed, while in 2022 and 2024, NSV dominated. This result confirms that during these periods, the share of "bad" risks in the portfolio increased, and

the risk distribution became asymmetric. Starting in 2023, the bank's transition to a diversification strategy and the restructuring of the portfolio by sector led to the balancing of risks once again.

These findings indicate that the bank's risk profile evolved from a more volatile and heterogeneously distributed risk structure toward a more stable and balanced one as a result of changes in its risk management strategies and portfolio restructuring over the analyzed period.

6. CONCLUSION

As a result, the empirical analysis indicates that the risk dynamics of Kapital Bank OJSC's loan portfolio over the period 2020–2024 evolved through three consecutive and clearly differentiated phases.

- The first phase (2020–2021) is characterized by a high level of risk and pronounced volatility in the loan portfolio. During this period, the formation of average risk indicators within the range of 3.1–3.2%, together with elevated values of variance and standard deviation, suggests an unstable risk profile. The predominance of downside semivariance over upside semivariance, along with a weakly asymmetric risk distribution, confirms the portfolio's heightened sensitivity to macroeconomic uncertainty and pandemic-related shocks.
- The second phase (2022) can be described as a transitional stage. Despite a decline in the average level of risk, the renewed increase in risk volatility, the dominance of downside semivariance, and the markedly negative skewness coefficient indicate that risks were primarily concentrated on the downside. The deepening of quarterly deviations reveals that the loan portfolio had not yet achieved full structural stabilization, resulting in an imbalanced risk distribution.
- The third phase (2023–2024) is characterized by a substantial reduction and stabilization of risk within the loan portfolio. In this period, the average risk indicator declined to the range of 1.4–1.8%, accompanied by a sharp decrease in standard deviation and a convergence of semivariance measures, indicating a more balanced and manageable risk structure. Changes observed in skewness and kurtosis coefficients further confirm that, compared to earlier periods, the portfolio became more resilient to extreme risk events.

Overall, the empirical findings demonstrate that risk behavior within the loan portfolio varies over time and that the assessment of risk should not rely solely on average indicators, but must also incorporate volatility, downside risk, and distributional characteristics. The results indicate that the risk-based management approaches implemented at Kapital Bank OJSC have contributed to the portfolio's attainment of a more stable and manageable structure in the post-pandemic period. At the same time, the high volatility and the dominance of downside risks observed during 2020–2022 underscore the need to further strengthen monitoring mechanisms for high-risk loan segments in future periods. In this context, the regular updating of risk forecasting models and the expansion of structural diversification of the loan portfolio may be considered appropriate measures to ensure the timely identification of risks and the mitigation of potential losses. Furthermore, the continued adoption of a prudent and selective lending approach for credit products that are more sensitive to macroeconomic fluctuations may contribute to enhancing the long-term risk resilience of the loan portfolio.

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