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Development of Financial Strategies Using Machine Learning for Right-Tail Value at Risk Estimation

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Abstract: In this study, we propose a novel methodology for strategic financial planning based on the assessment of right-tail value-at-risk (VaR) for interest rates under volatile market conditions. The core of the approach lies in the integration of three model types: classical (GJR-GARCH), machine learning (XGBoost), and deep learning (long short-term memory, LSTM). Each component targets a distinct dimension of risk: analytical structure, nonlinear dependencies, and complex temporal patterns, respectively. The results showed that the LSTM model delivered the highest forecasting accuracy under structural instability, achieving the lowest residual volatility ($\sigma \approx 0.0137$) and a high level of explained variance ($R^2 \approx 0.69$). An ensemble model (weighted 40% toward LSTM and 30% toward XGBoost) demonstrated superior reliability in risk estimation according to formal backtesting, along with the lowest average exceedance in VaR breaches. The practical value of the proposed approach is its ability to operate effectively under data scarcity and elevated volatility, enabling adaptive management of debt exposure. An elevated VaR level serves as a signal to restrict borrowing, while a low VaR opens opportunities for credit expansion. This model can be integrated into risk management systems of banking institutions and corporate finance departments as an effective tool for identifying, assessing, and mitigating right-tail risks during periods of economic instability.

Keywords: financial strategy, value-at-risk, GARCH, XGBoost, LSTM, credit risk

1. Introduction

Market conditions in which enterprises operate establish a permanent dependence on external financing. Borrowing plays a key role in the financial strategy, ensuring the continuity of operational activities and maintaining liquidity, which are necessary for effective functioning in the context of market uncertainty [1]. Given this, the foundation of a company's financial strategy is its constant need for borrowed funds.

Although the specific volumes, terms, and conditions of borrowing may vary depending on the current financial situation and market conditions, the need for external capital remains a constant requirement to maintain financial stability and the company's growth. Decisions regarding the attraction of borrowed funds are accompanied by the risk of changes in capital costs, driven by interest rate volatility and changing macrofinancial conditions. Under unfavorable market dynamics, debt servicing may exert pressure on cash flows, disrupting the financial balance of the company.

Under such conditions, the traditional interpretation of value-at-risk (VaR) as the probability of losses in a financial institution loses its universality [2]. In the case of debt financing, a critical risk emerges (i.e., right-tail risk), when the rate of increase in the cost of borrowed funds exceeds the rate of profit growth for the borrower. The standard VaR assessment, which focuses on the left tail of the distribution (i.e., losses), fails to adequately identify these threats.

Therefore, it is essential to improve the VaR methodology by focusing on right-tail breaches, which serve as markers of financial instability. To address this, it is advisable to adapt the approach to forecasting right-tail VaR by combining generalized sutoregressive conditional heteroskedasticity (GARCH) models, machine learning methods (XGBoost, long short-term memory [LSTM]), and historical estimates. This approach allows for more accurate identification of periods of increased risk and favorable moments for attracting borrowed funds, thus optimizing the company's financial strategy.

Hence, the goal of this study was to develop an adaptive methodology for forecasting right-tail VaR by integrating classical statistical and machine learning models for optimizing financing strategies, particularly identifying favorable periods for attracting borrowed resources in the context of volatile interest rates and asymmetric risks.

2. Literature Review

The need for external financing, driven by cash-flow gaps, is a decisive factor in a firm's financial strategy, as it directly influences decisions regarding capital structure, maturity, and instruments for raising funds [3, 4]. Under conditions of increasing economic turbulence and unstable cash flows, liquidity coverage policies require a synthesis of classical financial theories with modern tools of quantitative risk management.

A cash flow gap, when available cash inflows do not cover short-term obligations, acts as a financial trigger for raising additional financing. Forecasting stress gaps—those that exceed historical norms and may lead to defaults or credit rating downgrades—affects both the choice of financing instruments and the timing of market entry [5, 6]. Empirical evidence confirms that higher volatility of operating cash flows increases firms' reliance on short-term debt and raises refinancing risks, especially under tightening credit conditions [3].

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In this context, right-tail VaR is increasingly applied as an indicator of the probability that debt servicing costs will exceed a predefined level of financial resilience. Unlike classical VaR, which focuses on losses (the left tail of the distribution), the right-tail VaR analyzes scenarios in which a borrower loses control over the cost of funding—an issue of critical importance [7, 8]. Rising interest rates, tightening credit conditions, and increased debt servicing costs are empirically linked to greater corporate financial fragility and higher cost of external financing, reinforcing the role of right-tail VaR as an early warning signal [4, 9].

Recent advances in volatility and tail-risk modeling emphasize that traditional GARCH specifications tend to underestimate extreme right-tail realizations, particularly during periods of structural breaks and regime shifts. Studies based on hybrid and sentiment-augmented frameworks demonstrate that combining GARCH structures with deep learning architectures substantially improves the accuracy of VaR forecasts under stressed market conditions [10, 11]. These findings are particularly relevant for forecasting sudden increases in borrowing costs and liquidity stress.

Traditional GARCH models, based on normal or t-distributions, tend to underestimate the probability of extreme right-tail outcomes, leading to an underestimation of risks associated with sudden increases in borrowing costs. To address these limitations, recent studies propose models with heavier tails, as well as hybrid ensemble approaches that combine classical financial models with machine learning methods such as XGBoost, LSTM, or generative adversarial networks [12, 13, 14].

LSTM models, in particular, have attracted attention in forecasting right-tail VaR due to their ability to capture temporal dynamics and nonlinear dependencies in financial time series. Unlike statistical approaches, LSTMs provide adaptive learning based on historical interest rate fluctuations, uncovering hidden patterns that signal the approach of stress cash flow gaps [4, 15]. Recent empirical evidence confirms that deep neural networks significantly enhance the prediction of tail-dependent risk measures, including conditional VaR (CVaR), especially when combined with mixed-frequency data and penalized quantile regression techniques [14, 16].

Moreover, Bayesian and deep learning approaches applied to volatility indices, such as the VIX, highlight the importance of accounting for uncertainty in model parameters and latent regimes when forecasting extreme risk realizations [17]. These methods improve the robustness of forward-looking risk assessments and strengthen the informational content of VaR-based indicators for financial decision-making.

Caldara et al. [18] demonstrated that an ensemble model combining Historical VaR, GARCH, and machine learning techniques reduces the error of cash-stress risk estimation and improves the timing of financial decisions. Ensemble forecasting frameworks that explicitly model right-tail behavior and extreme scenarios are increasingly proposed as core components of early warning systems in corporate finance [13, 19].

Despite these advances, there is still no unified methodology that directly translates right-tail VaR signals into strategic decisions on the volume, maturity, and structure of external financing. Recent studies highlight the need for a formalized financial burden indicator that integrates forecasted cash flow gaps, firm-specific risk tolerance, and the expected cost of capital [5, 20]. Optimization-based approaches that embed tail-risk measures into financing and portfolio decisions provide promising directions but remain underexplored in the context of corporate liquidity management [16].

Thus, the right-tail VaR should be viewed not only as a risk management tool but also as a mechanism for the timing of financial decisions. The transition to integrated analytics of cash flow gaps and VaR metrics provides a foundation for enhancing operational flexibility, reducing the cost of capital, and strengthening firms' resilience to financial shocks.

3. Research Methodology

3.1. Risk assessment of excessive interest rate increases via right-tail VaR and feature engineering for regression

One of the key challenges in strategic corporate financial management is determining the optimal volume and timing of credit acquisition, taking into account interest rate dynamics. Market volatility complicates the assessment of the risk of excessive rate increases, which leads to higher financing costs. In view of this, the classical VaR approach, traditionally used to limit potential losses for the lender, has been refocused on the assessment of right-tail VaR, which reflects the probability of short-term rate increases that are unfavorable for the borrower. Formally, this can be described as

$$P(rt+1 > VaRt+1\alpha|Ft) = \alpha, \tag{1}$$

where $r_{t+1} = ln!\left(\frac{R_{t+1}}{R_t}\right)$ is the log-change of the short-term interest rate between periods (t) and ($t+1$); VaR^{α}_{t+1} is the threshold (quantile) value of the distribution of r_{t+1} at the confidence level $(1-\alpha)$, interpreted as the right-tail VaR; $\alpha\in(0,1)$ is the significance level (probability of exceedance); and $\mathcal{F}_t$ is the information set (σ-algebra) containing all available information at time (t).

The assessment of this risk involves modeling interest rate volatility, which lays the methodological foundation for managing credit acquisition and cash flow gaps. Given the non-stationarity of long-term interest rate series, a time series of their log-transformed values was used to build the model:

$$r_t = 100 \cdot \ln\left(\frac{P_t}{P_{t-1}}\right), \quad t = 1, \ldots, T, \tag{2}$$

where P_t is the short-term interest rate at day (t); P_{t-1} is the short-term interest rate at day ($t-1$); r_t is the daily log-return of the interest rate, expressed in percentage points; and T is the length of the time series (number of observations).

This allowed for variance stabilization and provided a sound basis for further modeling.

3.2. GARCH models: Conditional volatility and adaptive scaling

The first stage in modeling the conditional volatility of the log-transformed interest rate was the construction of a GJR-GARCH(1,2) model with an ARIMA(12,0) specification in the mean equation. This model accounts for asymmetric volatility effects, particularly the heightened sensitivity of financial time series to negative shocks. The model is formalized by the following system of equations:

Mean equation:

$$r_t = \mu_t + \varepsilon_t,$$
$$\mu_t = \phi_0 + \sum_{i=1}^{4} \phi_i r_{t-i}, \tag{3}$$

where r_t is the log change in the interest rate at time t; μ_t is the conditional mean; ϕ_0, ϕ_i are AR coefficients; and r_{t-i} are lagged values.
where r_t is the log-return of the short-term interest rate at time (t); μ_t is the conditional expectation of (r_t), modeled as an AR(4) process; ε_t is the error term (white noise) with zero mean and finite variance; ϕ_0 is the constant term; ϕ_i is the autoregressive coefficients ($i = 1, \ldots, 4$); and r_{t-i} is the lagged log-returns of the interest rate.

Error term:

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim D(0,1), \tag{4}$$

where ε_t is the stochastic component, σ_t is the conditional standard deviation, and z_t is an i.i.d. innovation from distribution D (Normal, Student's t, or Johnson SU).

Conditional variance:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 I(\varepsilon_{t-1} < 0)\varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2, \quad (5)$$

where ω is the base volatility level; α_1 captures reaction to past shocks; γ_1 reflects asymmetry ("bad news" effect); $I(\cdot)$ is an indicator function; and β_1, β_2 are volatility smoothing coefficients.

Right-tail VaR at confidence level 1− is calculated as:

$$\mathrm{VaR}_t^{\alpha} = \mu_t + q_{1-\alpha}^{(D)} \cdot \sigma_t, \quad (6)$$

where $q_{1-\alpha}^{(D)}$ is the $1 - \alpha$ quantile of the distribution D.

To improve the accuracy of risk assessment, volatility was dynamically scaled:

$$\tilde{\sigma}_t = s \cdot \sigma_t, \quad (7)$$

where $\tilde{\sigma}_t$ is the scaled volatility and ss is an iteratively calibrated scaling factor based on VaR exceedances during the validation period. This allowed the model to be adapted to the actual frequency of breaches during the control period.

3.3. Applying XGBoost regression for VaR forecasting

A key challenge in modeling Right-Tail VaR is the model's readiness to handle sudden structural shocks that lead to nonlinear patterns in temporal dynamics.

GARCH requires strict specification of conditional variance and residual distribution, which necessitates the search for more flexible approaches. One such relevant method is XGBoost regression, which offers several advantages:

1) The ability to train an ensemble of trees without distributional assumptions: Unlike parametric models, XGBoost does not require specifying the residual distribution or conditional variance, as it learns by minimizing a loss function:

$$\mathcal{L} = \sum_{i=1}^{n} (y_i - f(x_i))^2 + \sum_{m=1}^{M} \Omega(T_m), \quad (8)$$

where $f(x_i)$ is the ensemble prediction and $\Omega(T_m)$ is a tree complexity penalty.

2) Ability to capture complex nonlinear dependencies: XGBoost is a gradient boosting algorithm over decision trees that effectively detects
   a. interactions between lags r_{t-1}, r_{t-2}, r_{t-3};
   b. asymmetric effects (e.g., negative shocks have more severe consequences than positive ones);
   c. structural shifts in the time series (such as changes in monetary policy regimes or institutional transitions).

The ensemble of trees incrementally refines prediction errors, forming a nonlinear forecasting surface that adapts to local changes in the data. Thus, XGBoost regression is a flexible alternative to parametric models, particularly suitable for adaptive forecasting of right-tail risk. Its application involves a series of steps.

3.3.1. Feature engineering

Using the log-interest rate series (2), for each time $t \geq 4$, we construct a three-dimensional lag vector:

$$\mathrm{x}_t = \begin{pmatrix} \mathrm{r}_{t-1} \\ \mathrm{r}_{t-2} \\ \mathrm{r}_{t-3} \end{pmatrix} \quad (9)$$

where x_t is the regressor vector. The target variable is

$$y_t = r_t, \quad (10)$$

The dataset (x_t, y_t) is used to train the XGBoost model, enabling it to capture nonlinearities, asymmetries, and regime changes. After training, residual analysis and right-tail VaR estimation are conducted.

3.3.2. Regression formalization and residual volatility estimation

Training is performed on the period:

$$t = 4, \ldots, T - n_{\text{out}}, \quad (11)$$

where n_{out} is the length of the test period.

The residual vector is

$$\varepsilon_i = y_i - \widehat{r_1}, \quad i = 1, \ldots, n_{\text{train}}. \quad (12)$$

The residual standard deviation is computed as

$$\widehat{\sigma_\varepsilon} = \sqrt{\frac{1}{n_{\text{train}}} \sum_{i=1}^{n_{\text{train}}} \varepsilon_i^2}, \quad (13)$$

interpreted as the conditional volatility of the model.

3.3.3. Estimating right-tail VaR using XGBoost

The value of residual volatility $\widehat{\sigma_\varepsilon}$, obtained in Equation (13), is used as a key parameter for forecasting right-tail risk—that is, the potential excessive increase in interest rates, which is critically important for the borrower.

For a given confidence level $\alpha = 0.95$, the quantile of the standard normal distribution is introduced:

$$z_\alpha = \Phi^{-1}(\alpha), \quad (14)$$

where $\Phi^{-1}(\alpha)$ is the inverse function of the standard normal cumulative distribution function and z_α is the critical value corresponding to the confidence level α.

Based on the point forecast $\widehat{r_t}$ and the residual volatility $\widehat{\sigma_\varepsilon}$, the forecasted threshold increase in the interest rate in the form of VaR is defined as

$$VaR_t^{\alpha,\mathrm{XGB}} = \widehat{r_t} + z_\alpha \cdot \widehat{\sigma_\varepsilon}, \quad (15)$$

where $\mathrm{VaR}_t^{\alpha,\mathrm{XGB}}$ is the estimate of Right-Tail VaR based on XGBoost; $\widehat{r_t}$ is the forecasted log-transformed interest rate; and $\widehat{\sigma_\varepsilon}$ is the estimate of residual volatility.

Unlike parametric approaches, XGBoost-VaR accounts for local trends and allows the model to adapt to changes in market regimes without requiring specification of the residual distribution.

3.4. Application of LSTM for VaR forecasting

The complex nature of interest rate time series—their autocorrelation, structural breaks, nonlinearity, and heteroskedasticity—necessitates the use of recurrent neural networks (RNNs), particularly LSTM, for VaR estimation. This approach is novel in modeling risk values on the right tail of the distribution.

The key advantages of using LSTM as follows:

1) Handling long-term temporal dependencies: The “memory” mechanism allows LSTM to effectively model the impact of delayed effects on interest rate levels, unlike classical models that require explicit lag specification.
2) Adaptability to unstable conditions: Due to its ability to learn from observations with varying amplitude and volatility, LSTM remains robust to regime shifts and anomalies—critical under macroeconomic instability.
3) Integration of multifactor features: The network can simultaneously process multiple input features (e.g., rate lags, expectation indices, spreads, trading volumes), expanding the model’s analytical space without manual specification of functional forms.
4) Direct estimation of right-tail risks: LSTM training can be oriented toward forecasting VaR exceedances or residual risks, avoiding indirect assumptions about error distributions.

3.4.1. Model architecture and configuration

A single-layer LSTM model was tested, containing 64 neurons in the input layer. The model uses three-dimensional input data, including the time series X_t, which contains current values of the primary variable (e.g., interest rates), and auxiliary predictors $Z_t^{(1)}$ and $Z_t^{(2)}$, which may include economic factors such as inflation rates, exchange rate changes, and other macroeconomic indicators.

The logic of the model is not only to account for current time series values but also to process additional features that may influence future changes. This enables the model to adapt to shifts in market conditions, which is crucial for accurate financial risk forecasting.

This was formalized as follows:

$$\widehat{y_t} = \mathrm{LSTM}\left(X_t, Z_t^{(1)}, Z_t^{(2)}\right) \tag{16}$$

where $\widehat{y_t}$ is the predicted residual at time *t*.

One of the main advantages of the LSTM model is its ability to effectively process temporal dependencies, which is crucial for financial time series. It enables the retention of long-term relationships between events, helping to more accurately forecast future states. Thus, LSTM made it possible to detect trends or cycles based on historical data and adjust predictions in response to changes in macroeconomic indicators such as interest rate shifts or inflation.

For model training, the Huber loss function was selected, which reduces the impact of outliers. This is critically important for financial data, where extreme values—such as sudden rate spikes or economic crises—can distort predictions.

Huber loss is flexible, allowing the model to be less sensitive to outliers while maintaining efficiency at larger deviations from the true value. The loss function is defined as:

$$L_{\text{Huber}}\left(\widehat{y_t}, y_t\right) = \begin{cases} \frac{1}{2}\left(\widehat{y_t} - y_t\right)^2 \text{для} \left|\widehat{y_t} - y_t\right| \leq \delta \\ \left(\delta\left|\widehat{y_t} - y_t\right| - \frac{1}{2}\cdot\delta\right) \text{для} \left|\widehat{y_t} - y_t\right| > \delta' \end{cases} \tag{17}$$

where δ is the parameter that controls the transition between quadratic and linear loss.

The model was optimized using the Adam algorithm with a learning rate of $\alpha = 0.001$. Adam incorporates adaptive learning rate adjustment and momentum techniques, ensuring stable and fast training even with large datasets.

One of the key challenges in training deep neural networks is overfitting. To prevent this, dropout regularization with a probability of 20% was applied in order to reduce the risk of the model overfitting to the training data and improve its generalization capability.

To monitor model quality, the dataset was split into a training set (80%) and a validation set (20%) in order to evaluate the model’s performance on unseen data, which is essential for testing its ability to operate under real-world uncertainty.

The residual forecasts generated by the LSTM model are used to construct the conditional distribution of exceedances. This enables a more accurate estimation of the probability that future interest rate increases will exceed a critical threshold, given current economic conditions.

Right-tail VaR is calculated as the quantile of the conditional exceedance distribution:

$$\mathrm{VaR}_\alpha = \widehat{q_{1-\alpha}}, \tag{18}$$

where $\widehat{q_{1-\alpha}}$ is the (1-α)-quantile of the conditional exceedance distribution, which allows for determining the maximum potential loss at a given confidence level α.

The application of the LSTM model in this study not only improved forecast accuracy but also significantly enhanced the reliability of risk assessment through right-tail VaR. Incorporating additional economic factors via auxiliary predictors enables the model to adapt to diverse market conditions, which is essential for making well-informed financial decisions. Thanks to the model’s ability to retain long-term dependencies and handle outliers, it serves as a powerful tool for forecasting financial risks under unstable conditions.

3.5 Construction of an ensemble model for right-tail VaR estimation

To improve the forecast of right-tail VaR, a hybrid model was applied that integrates multiple approaches: empirical (historical), parametric (GARCH), and nonlinear (XGBoost and LSTM). This integration allowed the model to better adapt to changing market conditions and stabilize forecasting accuracy. The combined right-tail VaR estimate represents a linear aggregation of the results obtained from each component. This approach ensures a balanced weighting across different models, leveraging their respective strengths:

$$\begin{aligned} \mathrm{VaR}_t^{\mathrm{comb}} = w_1 \cdot \mathrm{VaR}_t^{\mathrm{Hist}} + w_2 \cdot \mathrm{VaR}_t^{\mathrm{GARCH}} \\ +3 \cdot \mathrm{VaR}_t^{\mathrm{XGB}} + +w_4 \cdot \mathrm{VaR}_t^{\mathrm{LSTM}}, \end{aligned} \tag{19}$$

where $\mathrm{VaR}_t^{\mathrm{comb}}$ is the combined estimate of right-tail VaR at time *t*; $\mathrm{VaR}_t^{\mathrm{GARCH}}$ is the VaR estimate obtained from the GARCH conditional volatility model; $\mathrm{VaR}_t^{\mathrm{XGB}}$ is the VaR estimate derived using the XGBoost model; $\mathrm{VaR}_t^{\mathrm{Hist}}$ is the empirical VaR estimate based on the historical approach; $\mathrm{VaR}_t^{\mathrm{LSTM}}$ is the VaR estimate obtained using the LSTM model; and w_1, w_2, w_3, w_4 are the weighting coefficients for each model, reflecting the degree of confidence in each ensemble component.

3.5.1 Determination of Weighting Coefficients

The weights are assigned based on the relevance of each model to the specific context. The ensemble components were assigned the following weights:

1) $w_1 = 0.1$ for the historical approach, used as an empirical benchmark;
2) $w_2 = 0.2$ for the GARCH model, which provides a stable volatility estimate but does not capture nonlinear relationships;
3) $w_3 = 0.3$ for XGBoost, which has a strong ability to adapt to complex and nonlinear dependencies in the data;
4) $w_4 = 0.4$ for the LSTM model, which captures long-term dependencies in time series and offers flexibility in adapting to various market conditions.

This hybrid construction enables precise estimation of right-tail VaR and supports optimized financing decisions by accounting for both structural risks and current market dynamics.

3.6. Backtesting and validation of the combined model

To validate the right-tail VaR forecasts from the combined model (16), a backtesting procedure is applied.

VaR breach indicator:

$$I_t = \begin{cases} 1, \; if \; \mathrm{r\_t} > \mathrm{VaR_t^{comb}} \\ 0 \end{cases} \mathrm{t = T - n_{out} + 1, \ldots, T}, \quad (20)$$

Empirical exceedance rate:

$$\pi_{\text{emp}} = \tfrac{1}{n_{\text{out}}} \textstyle\sum_{t=T-n_{\text{out}}+1}^{T} I_t, \quad (21)$$

To test H_0:$\pi_{\text{emp}} = \alpha$, the Kupiec POF test is applied:

$$LR_{\text{POF}} = -2ln\left[(1-\alpha)^{n_0}\alpha^{n_1} / (1-\pi_{\text{emp}})^{n_0}\pi_{\text{emp}}^{n_1}\right], \quad (22)$$

where $n_1 = \sum I_t$, and $n_0 = n_{\text{out}} - n_1$.

If $LR_{\text{POF}} < \chi^2_{1,0.95}$, we do not reject H_0; the model is statistically consistent with the expected exceedance rate. To check temporal independence of exceedances, the Christoffersen test may be used.

Empirical validation uses real data from the Ukrainian banking sector. The next section outlines the data structure, sampling parameters, and modeling results, demonstrating the effectiveness of the proposed approach under macroeconomic turbulence.

4. Results and Observations

4.1. Source data and justification for the selected period

The empirical basis of the study is the daily dynamics of interest rates on loans issued to legal entities by Ukrainian banking corporations over the period from January 3, 2020, to February 23, 2022 [21]. The data were obtained from the official website of the National Bank of Ukraine (Figure 1a and 1b[1]). The restriction of the study period to February 23, 2022, is due to the onset of the active phase of hostilities on the territory of Ukraine and the radical transformation of the economic environment, including changes in the mechanisms of interest rate formation, refinancing, and monetary policy in the banking sector.

4.2. Stationarity testing and transformation

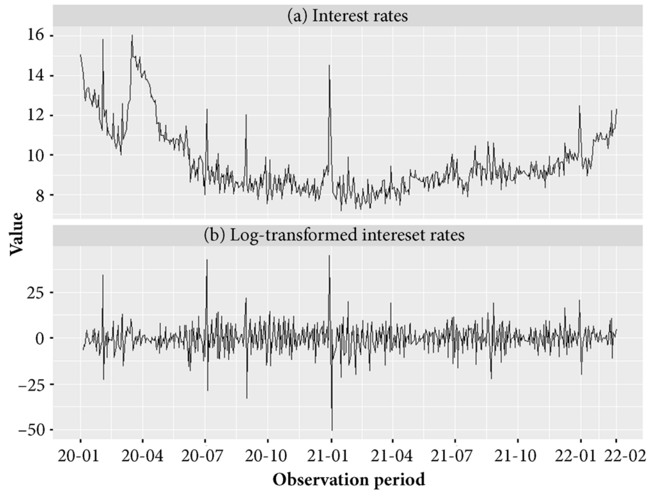
To ensure the correctness of the modeling process, the stationarity of the interest rate time series and its log-returns was assessed using the Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests. The results indicated that the original series is non-stationary (ADF: $p = 0.6051$; KPSS: $p < 0.01$), suggesting it is integrated of order one.

After computing the log-differences, a stationary series was obtained (ADF: $p < 0.01$; KPSS: $p > 0.1$), which is suitable for constructing conditional volatility models (Figure 1b).

4.3. Baseline model: Historical simulation

Following the stationarity verification of the log-returns of interest rates, a historical simulation (HS) model was constructed to serve as a benchmark for risk estimation. The model was implemented

Figure 1
Dynamics of average interest rates on loans to Ukrainian enterprises (a) and the corresponding log-changes of these rates (b) from January 3, 2020 to February 23, 2022



using a rolling window of 250 days, a 1-day forecasting horizon, and a confidence level of 95%.

The actual proportion of VaR exceedances amounted to 4.8%, closely aligning with the theoretically expected 5%. This result was confirmed by the Kupiec Proportion of Failures (POF) test (*p*-value = 0.88), indicating the empirical accuracy of the VaR estimation.

While the HS model provides a valid reference for VaR estimation, it exhibits limited adaptability to abrupt changes in volatility due to the absence of learning mechanisms. Given this lag in responsiveness, HS was used as a referential model.

To enhance forecasting precision and flexibility, the study proceeded with an analysis of the prerequisites for applying GARCH-type approaches. A GJR–GARCH model was constructed to account for asymmetric volatility effects. Subsequently, nonlinear methods such as XGBoost and LSTM were employed, enabling the capture of complex temporal and structural dependencies in the data.

Figure 1 illustrates both the overall trend in the cost of credit resources and the volatility of the time series, which is used as input data for the estimation of right-tail VaR.

4.4. Assessment of preconditions for applying GARCH

To determine the suitability of applying a GARCH model, diagnostic tests were conducted to evaluate the presence of autoregressive conditional heteroskedasticity and autocorrelation in the residuals. Specifically, Engle's ARCH Lagrange Multiplier (LM) test was used to detect autocorrelated variance, while the Ljung–Box test was applied to assess residual autocorrelation (Table 1).

The high test statistics and extremely low *p*-values from the previous diagnostics confirm the presence of conditional heteroskedasticity and autocorrelated variance, thereby validating the applicability of GARCH-type models.

Table 1
Heteroskedasticity assessment of the log-interest rate series

Test	Statistic	p-value	Conclusion
ARCH LM (12 lags)	113.59	< 2.2e-16	Strong ARCH effect
Box–Ljung (10 lags)	146.26	< 2.2e-16	Variance autocorrelation present

[1] Author's own calculations in RStudio 2025.07 based on data from https://bank.gov.ua.

Table 2
Parameters of asymmetric GARCH(1,1) models

Model	α_1	β_1	γ_1	ω	Shape	Skew	Distribution Type
GARCH – Normal	0.600	0.531	–0.264	6.600	–	–	Normal
GARCH – t	0.745	0.544	–0.668	21.900	2.49	–	Student's t
GARCH – JSU	0.447	0.562	–0.311	12.700	1.13	0.447	Johnson SU

Notes: The parameters α_1, β_1, γ_1, and ω are coefficients of the GJR–GARCH(1,1) model. The Shape and Skew parameters are included only for distributions that support them (Student's t, Johnson SU).

4.5. Risk estimation using the GJR–GARCH(1,1) model with different residual distributions

Based on these findings, three variants of the GJR–GARCH(1,1) model were implemented. This model captures the asymmetric response of volatility to market shocks—a key feature for modeling the leverage effect. All three specifications share the same structural form but differ in the assumed distribution of residuals:

1) **Normal distribution**: serves as a baseline but may underestimate tail risk
2) **Student's t-distribution**: better suited for capturing heavy tails, enhancing VaR accuracy under extreme market conditions
3) **Johnson SU distribution**: a flexible alternative capable of modeling both skewness and kurtosis, thus accommodating asymmetric and heavy-tailed behavior simultaneously

This setup enabled an assessment of how the choice of residual distribution affects the precision of VaR estimates and the model's adaptability to unstable market regimes.

The models were estimated using the maximum likelihood method based on the log-return series of short-term interest rates (Table 2).

The specifications of GJR–GARCH(1,1) confirmed the presence of asymmetry ($\gamma_1 < 0$) and the leverage effect, an amplified volatility response to negative market shocks. The most pronounced asymmetric effect is observed in the model with the JSU distribution (γ_1 = –0.311), indicating its ability to accurately reflect market dynamics. In the t-model, a high value of β_1 (0.544) is observed with a weak immediate response (α_1 = 0.745), which indicates volatility inertia. The parameters shape = 1.13 and skew = 0.447 for JSU confirm heavy tails and asymmetry, which is relevant for risk modeling in an unstable environment.

Comparison of the three GJR–GARCH(1,1) specifications showed that the Kupiec test for the expected risk level was passed only by the models with normal and t-distribution (p = 0.3294 and p = 0.4812, respectively), while the Johnson SU model had a statistically significant deviation (p = 0.0029) and an excessive frequency of breaches. At the same time, the asymmetry, heavy tails, and distributional skewness inherent in JSU provide greater modeling flexibility. Therefore, despite formally failing the breach frequency test, the JSU model was selected for further VaR modeling, as its structural flexibility allows for better reproduction of real risks than other alternatives.

4.6. Use of XGBoost regression for risk estimation based on

The next stage of the study involved the application of the boosting algorithm (XGBoost), which combines an ensemble of decision trees with loss function optimization. Its advantage lies in the ability to detect complex nonlinear dependencies without the need for formal assumptions regarding data distribution or the functional form of the model (Table 3).

Table 3
Key parameters of the XGBoost regression model

Parameter	Value	Comment
Number of trees	50	Balance between accuracy and overfitting risk
Average tree depth	≈6	Detection of nonlinear patterns without excessive complexity
Loss function type	Mean squared error	Standard function for regression tasks
Regularization (λ, γ)	$\lambda = 1.0$, $\gamma = 0.1$	Model complexity control, reduction of overfitting risk
Input features	r_{t-1}, r_{t-2}, r_{t-3}	Lagged values of log-returns of interest rates
Target variable	r_t	Forecasted log-returns of interest rates
Forecast accuracy	$R^2 = 0.72$	Determined on the validation set
Residual volatility	$\widehat{\sigma_\varepsilon} = 0.014$	Used for VaR estimation

Note: The model was trained on the period $t = 4, \dots, T-n_{out}$, followed by testing on the last n_{out} observations. Regularization parameters were selected empirically through cross-validation.

The configuration of the XGBoost model with moderate tree depth, optimal number of trees, and regularization ensures an effective balance between forecasting accuracy and resistance to overfitting. Backtesting results confirm the reliability of the model: the actual number of breaches (13) almost coincides with the expected (12.5), and the p-value of the Kupiec test (0.8853) indicates statistical compliance of the model with the given risk level. The average VaR value is 10.3256, with a standard deviation of 5.4328, a minimum value of –0.5602, and a maximum of 44.5817, demonstrating the model's ability to adapt to a wide range of market conditions.

4.7. Right-tail risk estimation using the LSTM neural network

The foundation of time series modeling is based on linear or weakly nonlinear approaches that assume stationarity, normality, or heteroskedastic dependence of residuals. However, real financial data, particularly short-term interest rates, are characterized by high instability, regime shifts, latent trends, and seasonal effects. Under such conditions, models capable of adapting to changes in statistical properties without the need for fixed parametric assumptions are effective.

One of the most promising directions for solving this task is the use of deep learning, particularly RNNs of the LSTM type, which have the ability to memorize and accumulate information over long time intervals. First proposed by Hochreiter and Schmidhuber [22], the LSTM architecture is one of the fundamental elements of time series modeling in machine learning. It has three types of "gates" (input, forget, and output) that allow control over the amount of information stored or updated in the internal environment. In financial analytics, this enables the capture of both short-term fluctuations related to market noise and long-term trends or seasonal cycles.

The application of LSTM for right-tail VaR estimation becomes particularly important in the context of the risk of a sharp increase in interest rates, which is critical for financial strategy development. The LSTM model was trained on the log-return series of short-term rates, represented as lagged predictors: $(r_{t-1}, r_{t-2}, r_{t-3})$. The lags were selected based on the autocorrelation structure, which revealed significant dependencies within a three-day time horizon. Subsequently, the data were scaled using Min–Max normalization to convert values into a unified interval [0,1], which helps avoid dominance of variables with high dispersion.

At the next stage, Z-score standardization (centering and scaling by standard deviation) was applied to stabilize the training of the LSTM model, ensuring equal influence of predictors. The data array was transformed into a tensor of format [N × 1 × 3], where N is the number of observations, 1 is the size of timesteps, and 3 is the number of features. The training and test sets were split in a ratio of 80:20. The LSTM model was implemented using the keras/tensorflow framework in the RStudio 2025.05.1 environment. It has a single-channel structure without layer stacking, which minimizes the risk of overfitting (Table 4).

Table 4
LSTM model architecture

Component	Configuration	Purpose
Input features	$(r_{t-1}, r_{t-2}, r_{t-3})$	Representation of temporal dynamics
Data format	[samples × 1 × 3]	One-step forecast
LSTM layer	64 neurons	Memorization of temporal patterns
Output Dense layer	1 neuron	Regression forecast ($\widehat{r_t}$)
Loss function	Mean squared error	Minimization of the difference between prediction and observation
Optimizer	Adam	Flexible model weight updating
Epochs	20	Total number of training iterations
Batch size	32	Number of observations per update cycle
Validation split	0.2	Percentage of data for validation

The model trained stably, with a gradual decrease in the loss function on both the training and validation sets, indicating the absence of overfitting. A reduction in validation error was observed up to the 15th epoch, after which the curve stabilized.

Based on the predicted values $(\widehat{r_t})$, residuals were calculated as $(\varepsilon_t = r_t - \widehat{r_t})$, which served as the basis for estimating the right-tail VaR at the 95% confidence level. The quantile of the residual distribution was determined empirically: $(q_{0.95} \approx 0.0231)$, which yields the formula for estimation:

$$\mathrm{VaR}_{0,95}^{\mathrm{LSTM}} = \widehat{r_t} + 0,0231. \tag{23}$$

This estimate reflects the risk of an unexpected increase in interest rates above the forecasted level. On the test set (107 observations), the actual number of breaches amounted to six cases, that is, 5.6% of observations exceeded the VaR threshold. This corresponded to the expected level of 5% and was confirmed by statistical tests: the p-value of the Kupiec test was 0.777, which did not reject the hypothesis of correct estimation. Thus, LSTM successfully passed the backtesting verification.

The root mean squared error (RMSE) was 0.0091, which indicated a low variation between the forecast and actual values, and the coefficient of determination ($R^2 \approx 0.69$) pointed to a notable ability of the model to reproduce short-term market dynamics. The estimated residual volatility was $\widehat{\sigma_\varepsilon} \approx 0.0137$, which was comparable to that of the GARCH model and also close to the results of XGBoost, where residual volatility was ≈ 0.014.

Among the advantages of using LSTM in the context of right-tail VaR estimation, the following should be noted:

1) absence of requirements for assumptions about the residual distribution (unlike GARCH);
2) automatic detection of latent temporal patterns (unlike XGBoost);
3) high resilience to regime shifts and changes in market dynamics;
4) flexibility in processing data of various scales and quality;
5) potential for further expansion to multifactor or multichannel models.

These properties make LSTM a valuable component in the ensemble risk assessment structure. The LSTM model confirmed its ability to accurately reproduce the dynamics of short-term changes in log-returns of interest rates, with high forecasting accuracy and correct estimation of right-tail VaR. Its residual volatility is stable, and the model adequately passes backtesting. Considering its ability to adapt to complex data structures and the limitations of other methods, LSTM is advisable to use as a source of VaR estimates under market instability, particularly in combination with other approaches within hybrid or ensemble structures.

4.8. Construction of an ensemble model for right-tail VaR estimation

To improve the accuracy of risk estimation and ensure adaptability to an unstable market environment, an integrated ensemble model of right-tail VaR was implemented, a combination of four independent sources of forecasting based on different assumptions and modeling techniques: historical simulation ($\mathrm{VaR}_t^{\mathrm{Hist}}$), GARCH conditional volatility model ($\mathrm{VaR}_t^{\mathrm{GARCH}}$), XGBoost regression ($\mathrm{VaR}_t^{\mathrm{XGB}}$), and LSTM regression ($\mathrm{VaR}_t^{\mathrm{LSTM}}$). In a formalized form, it can be represented as a weighted linear combination of the specified components:

$$\begin{aligned}\mathrm{VaR}_t^{\mathrm{ensemble}} = 0,10 \cdot \mathrm{VaR}_t^{\mathrm{Hist}} + 0,20 \cdot \mathrm{VaR}_t^{\mathrm{GARCH}} \\ +0,30 \cdot \mathrm{VaR}_t^{\mathrm{XGB}} + 0,40 \cdot \mathrm{VaR}_t^{\mathrm{LSTM}}.\end{aligned} \tag{24}$$

The LSTM model received the highest weight (40%), as it provided the lowest residual variance and stability of forecasts under changing market conditions. XGBoost (30%) also demonstrated high flexibility by capturing complex nonlinear relationships in financial time series [12], while GARCH (20%) offered a robust structural estimate based on conditional heteroskedasticity theory [23], and HS (10%) complemented the ensemble with sensitivity to local jumps.

Table 5
Backtesting metrics of VaR models (Level – upper 5%)

Model	Viol.	Exp.	p (Kupiec)	p (Christoffersen)	Mean VaR	SD VaR	Min	Max
GARCH	24	12.5	0.00289	0.291	9.93	2.01	6.78	18.2
XGBoost	13	12.5	0.885	0.251	11.5	2.98	7.91	21.4
Historical	12	12.5	0.884	0.270	10.2	1.72	8.14	15.6
LSTM	6	12.5	0.0000141	0.0738	12.1	3.04	8.33	23.7
Ensemble	18	12.5	0.133	0.0938	10.6	1.69	8.25	17.9

Note: Viol. – actual number of exceedances over 5% VaR; Exp. – expected number of exceedances (0.05 × Obs); p (Kupiec) – p-value for the Unconditional Coverage test; p (Christoffersen) – p-value for the Conditional Coverage test; Mean VaR – average forecasted VaR; SD VaR – standard deviation of predicted VaR; Min/Max – minimum/maximum predicted VaR.

The following parameters were used in the implementation:

1) (n_{out} = 250): length of the test period;
2) (VaR_{LSTM}): scalar estimate repeated across the entire test window;
3) all components normalized to the level of log-rates.

Thus, the ensemble model provides a combination of parametric, machine learning, and empirical estimates, allowing for greater stability and accuracy in assessing right-tail VaR under conditions of limited data and high volatility. This approach is consistent with the findings of Gu et al. [24], who demonstrate that machine learning methods significantly enhance predictive performance in financial risk and return forecasting by capturing complex nonlinear relationships and interactions that are difficult to model using traditional econometric techniques.

4.9. Evaluation of the effectiveness of right-tail VaR estimates using the ensemble model

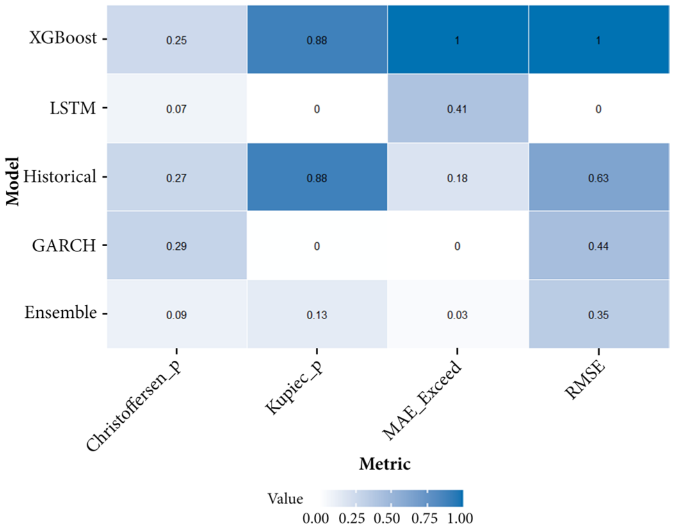
A key stage of the study was the comparative evaluation of the effectiveness of the 95% right-tail VaR. Based on the results of the Kupiec UC and Christoffersen CC tests, an analysis was conducted of calibration quality, forecast stability, and distribution characteristics of VaR estimates. It confirmed the advantages of the ensemble approach, which combines the predictive properties of GARCH, LSTM, XGBoost, and HS models over traditional and machine-learning-oriented models that served as components of the integrated structure. The results are presented in Table 5, which summarizes the key backtesting metrics for each model.

It is worth noting the compromise between the opposing characteristics of the base models—the stability inherent in HS model, the sensitivity to structural shifts in LSTM, the statistical consistency in XGBoost, and the analytical rigor in GARCH. Specifically, the ensemble showed 18 breaches against an expected 12.5 and had a p-value of 0.133 according to the Kupiec UC test, indicating no statistically significant deviation in the breach frequency. Additionally, the p-value for the Christoffersen CC test was 0.0938, meaning the breaches do not exhibit a tendency toward clustering.

Finally, the ensemble demonstrates the lowest variance in VaR estimates (SD = 1.69), outperforming HS (SD = 1.72), which is typically considered a benchmark for stability. Thus, the model ensured high smoothness and consistency of forecasted values while maintaining the ability to respond to extreme events. For clarity, RMSE and MAE were normalized within the interval [0;1], whereas the original scale was preserved for p-values (Figure 2).

This allowed for the following conclusions:

Figure 2
Heatmap of VaR model performance metrics



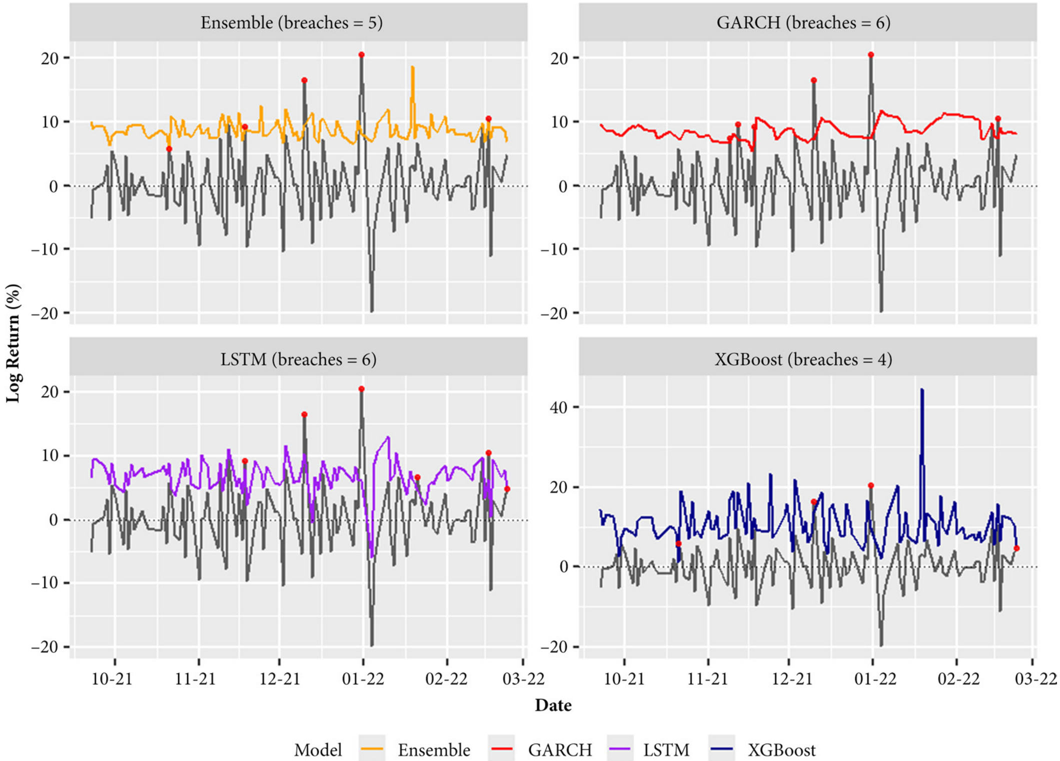
1) The ensemble model demonstrated a combination of accuracy and compliance with regulatory requirements, despite the fact that individual components—particularly XGBoost—have higher p-values for the Kupiec UC and Christoffersen CC tests, although they lag in accuracy (highest RMSE).
2) The LSTM model was characterized by the lowest RMSE (~9.29) and MAE (~4.71), but it significantly underestimated the number of breaches (p ≈ 0.0000141), although it can be recalibrated before further application.
3) GARCH and HS provided boundary estimates—either excessive breach frequency (for GARCH) or insufficient sensitivity to volatility (for HS).
4) XGBoost, although demonstrating high statistical consistency, obtained the highest errors in VaR estimation in both absolute and root mean square terms.

Thus, the ensemble model has proven its practical value as a tool for adaptive right-tail risk assessment, capable of adjusting to different volatility regimes without significant losses in accuracy and stability. It is a strong candidate for serving as a baseline model in strategic financial planning under conditions of high uncertainty. These properties become especially evident when analyzing the dynamics of actual log-returns of interest rates and the corresponding forecasted VaR values. For this purpose, test period indicators were visualized (Figure 3[2]).

The analysis indicates that the forecasted VaR boundaries for the ensemble, LSTM, GARCH, and XGBoost overlap with actual

[2] Author's own calculations in RStudio 2025.07 based on data from https://bank.gov.ua.

Figure 3
Forecasted right-tail VaR versus actual log-changes in interest rates for loans to Ukrainian enterprises from June 19, 2021 to February 23, 2022



Note: The number of exceedances shown in Figure 3 may be smaller than the values reported in Table 2, since the graph is based on a restricted data sample. The points indicate only those violations where `exceed = TRUE`, depending on the actual VaR calculation for this segment of the series.

rates, demonstrating how each model responds to market changes, particularly during moments of extreme volatility caused by economic shocks such as inflation expectations in August 2021 and other financial disturbances.

Compared to others, the ensemble model, which includes a significant share of the LSTM neural network (40%), showed higher adaptability to changes in the market environment, combining the stability of classical methods with the flexibility of machine learning. It is distinguished by the lowest number of exceedances among all models (3.90) and at the same time a relatively high trigger frequency (0.068). This indicates timely expansion of the VaR channel in response to market volatility without unnecessary loss of accuracy.

At the beginning of the test period (June–July 2021), when volatility remained low, the ensemble formed a narrow but effective VaR channel. Excessive reserving was avoided while ensuring protection: only isolated breaches were recorded. Meanwhile, GARCH(1,1) and XGBoost, although having lower breach frequencies (0.06 and 0.052 respectively), showed higher average exceedances (4.74 and 6.03), which potentially indicates less accurate accounting for tail risks.

Particularly illustrative is the period from August to October 2021, when the market experienced a series of macroeconomic shocks. The ensemble model, thanks to the significant contribution of LSTM, timely adapted the VaR boundaries, keeping the breach rate within 1–2 per month. LSTM as a standalone model recorded the lowest absolute number of breaches—only six for the entire period—and showed an average exceedance similar to GARCH (4.74), but with a lower frequency. This confirms that deep learning has a higher ability to detect non-trivial nonlinear dependencies and responds more quickly to structural shifts in the data.

During peak volatility periods (November–December 2021), the ensemble model continued to effectively scale risk boundaries in accordance with market changes. Although it recorded 17 breaches (the highest among all), this was accompanied by the lowest losses upon exceedance (mean_excess = 3.90), indicating a high level of control over risk magnitude. In contrast, GARCH or XGBoost, although having fewer breaches, showed significantly stronger violations when they occurred, posing greater risks in real-world conditions.

Thus, the distribution and nature of breaches confirm that the ensemble model best maintains the balance between market sensitivity and restraint against false signals. It provides not only a lower average exceedance size but also lower variance in estimates (SD ≈ 1.69), enabling more effective risk management and financial planning. Visual analysis confirms these conclusions—the constructed channels are more stable and better reflect the actual market profile, showing fewer chaotic triggers. Therefore, the combination of statistical models and deep learning methods in the ensemble architecture allows achieving a high level of adaptability without loss of accuracy, making it extremely effective for strategic risk management under uncertainty.

The use of LSTM within the ensemble VaR model improves the technical characteristics of the forecast and provides strategic advantages in risk management under economic instability and high market volatility. The LSTM model, integrated into the ensemble with GARCH and XGBoost, demonstrated the ability to adapt effectively, showing significant flexibility in forecasting tail risks and short-term fluctuations.

The VaR forecasting results for the LSTM model proved to be more stable and adaptive under different market phases, including periods of high volatility, which are typical for financial shocks. For example, during peak market fluctuations (November–December 2021), LSTM responded quickly to changes, maintaining forecast accuracy and minimizing the number of breaches. This is an important characteristic, as forecast accuracy of VaR is critically important for timely decision-making during market shocks. To verify the proposed approach, it was compared with the results of other studies using deep learning and hybrid VaR forecasting models, including Bao et al. [25]; Fischer & Krauss [15]; Kakade et al. [12]; and Wang et al. [26].

These sources provide representative performance indicators of similar traditional and hybrid models. According to the study by Kakade et al. [12], based on classical GARCH and LSTM, 18 breaches were recorded at a 5% confidence level (6.9%) with forecast variability SD VaR = 2.1. This indicates moderate model effectiveness under high volatility and less stable forecasts compared to the ensemble approach.

Table 6
Comparative effectiveness of right-tail VaR forecasting: Results of the proposed model and previous studies

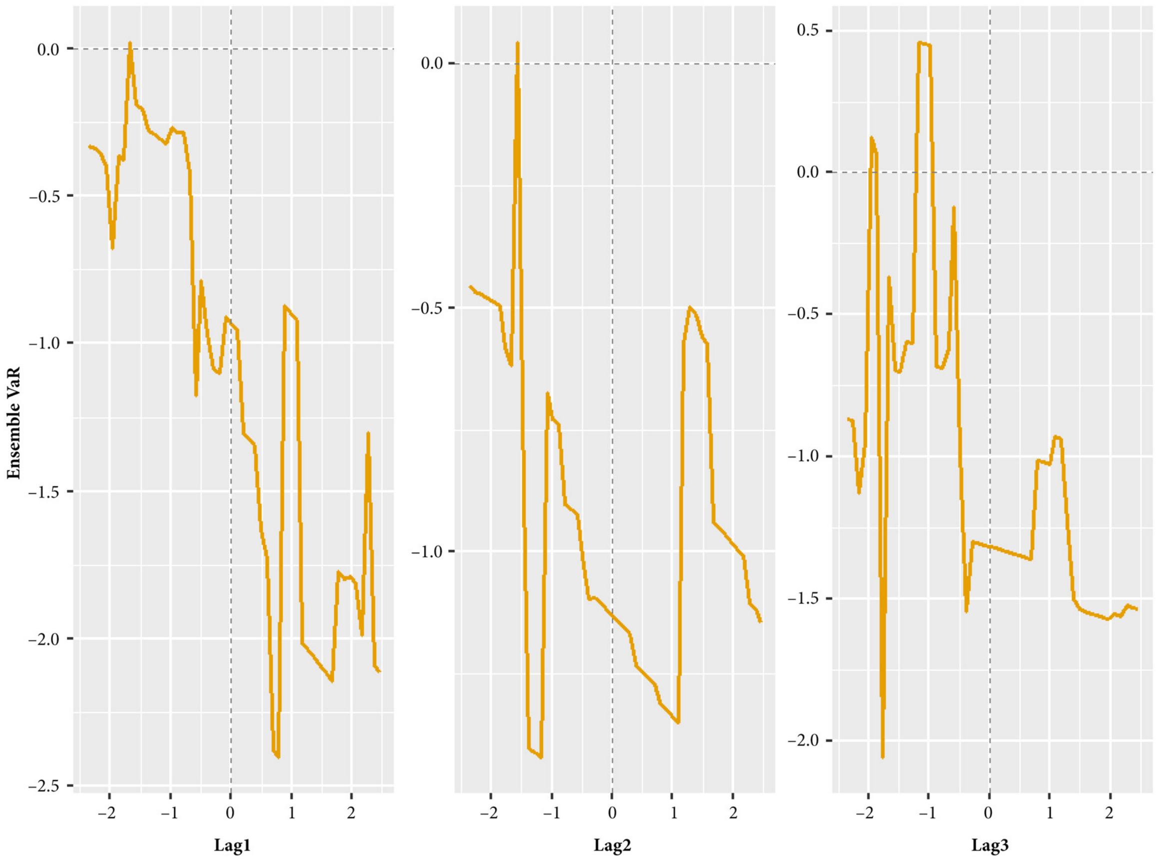
Author / Study	Breaches (%)	SD VaR	Forecast VaR Interval
Proposed model	3.6	1.69	[8.25; 17.9]
Bao, Yue, & Rao [2]	6.9	2.1	[8.0; 14.5] (approximate)
Fischer & Krauss [10]	6.0	n/a	[8.9; 15.3]
Kakade, Jain, & Mishra [15]	4.6	2.5	[7.8; 15.0] (approximate)
Wang, Wang, Lv, & Jiang [26]	5.0	n/a	[7.5; 14.0]

In the study by Bao et al. [25], the model produced 12 breaches (6%) with a VaR interval of [8.9; 15.3]. Despite better accuracy compared to that of Fischer & Krauss [15], the interval width turned out to be limited, complicating full coverage of extreme market events. In contrast, the proposed ensemble model shows a lower breach frequency (3.6%) and a significantly wider VaR interval [8.25; 17.9], indicating its advantage in risk-oriented coverage.

The GARCH-FHS+LSTM model used in Christodoulou-Volos [27] shows 14 breaches (4.6%) and forecast dispersion around 2.5. Despite its overall stability, it lags behind the proposed model in terms of variability, and therefore the tested ensemble model has a lower standard deviation of forecasted VaR (1.69), indicating higher consistency of results. Additionally, according to Wang et al. [26], the classical GARCH model recorded 20 breaches (5%) with a VaR interval of [7.5; 14.0]. The results presented in Table 6 once again demonstrate the limitations of traditional models in capturing potentially extreme values, especially under conditions of high market volatility.

The ensemble model demonstrated the lowest violation rate compared to established benchmarks, indicating its superior accuracy in right-tail risk assessment. The standard deviation of VaR within 1.69 confirms the stability of forecasts under varying market conditions, while the width of the coverage interval allows for the consideration of extreme scenarios. To evaluate the model's predictive sensitivity,

Figure 4
Partial dependence plots of the ensemble VaR model on lagged predictors (Lag1, Lag2, Lag3) from June 19, 2021 to February 23, 2022



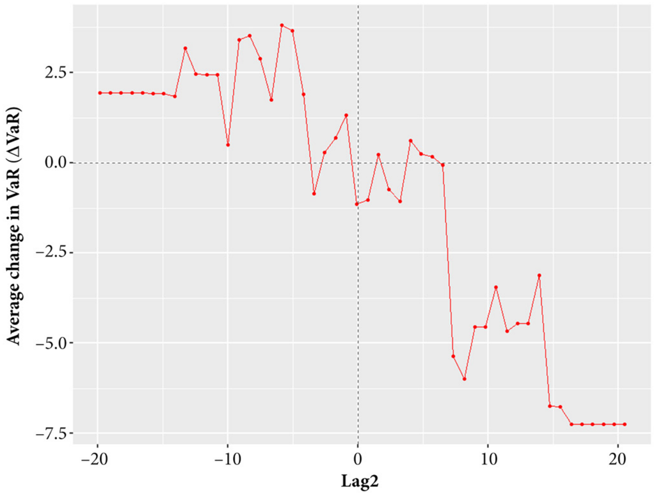
Note: The plots illustrate the isolated effect of each lagged variable on the forecasted VaR, holding other predictors at their average levels. This allows assessment of the model's sensitivity to short- and medium-term dynamics.

we conducted a partial dependence plot (PDP) analysis and a ΔVaR assessment by varying individual predictors (Figure 4[3]).

This analysis made it possible to identify the specific influence of lagged variables on the forecasted VaR. In particular, Lag1 shows a stable downward trend, reflecting the model's immediate response to the most recent market changes. Lag2 exerts the strongest effect: a reduction in VaR of approximately 11.1 points within the range [−19.87; 20.53] highlights its key role in modeling medium-term inertia. Lag3 reveals a complex nonlinear relationship, confirming the model's ability to adapt to extreme market scenarios.

For a quantitative assessment of Lag2's impact, a ΔVaR analysis was performed, which confirmed its significance in modeling volatility. The change in forecasted VaR ranged from +3.82 to −7.25, with a median of 0.24 and a mean of −1.03. The smooth and monotonic shape of the ΔVaR curve indicates the model's stability and its ability to adapt gradually to local variations in input features (Figure 5).

Figure 5
ΔVaR analysis for lag2: Impact on ensemble VaR (June 19, 2021 to February 23, 2022)



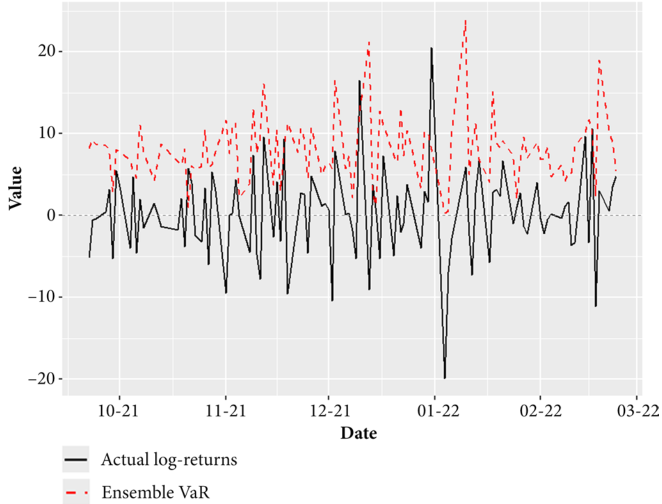
A comparison of forecasted VaR with actual log-returns of the interest rate confirmed the model's ability to capture both extreme and minimal risks. The maximum value of (VaR_{ens}) (23.87) exceeded the corresponding log-return (20.53), while the average (VaR_{ens}) (7.91) compared to the average log-return (0.27) reflected the expected asymmetry of right-tail risk assessment. The minimum value of (VaR_{ens}) (≈9.29) also exceeded the minimum log-return (−19.87), indicating adequate prediction of lower risk bounds. The standard deviation of (VaR_{ens}) (σ = 5.62) was lower than that of the actual series (σ = 6.62), confirming reduced variability of forecasts (Figure 6).

The number of exceedances of actual log-returns over the forecasted (VaR_{ens}) was minimal: in only 5% of cases did the log-return exceed VaR by more than one point. This demonstrates the model's ability to provide effective risk coverage. The observed asymmetry and excess kurtosis further confirm the relevance of right-tail risk assessment.

In summary, the LSTM component of the ensemble acts as a sensitive detector of short- and medium-term dependencies. The prominent role of Lag2, confirmed by both PDP plots and ΔVaR analysis, makes it the primary driver of inertia risk, while Lag1 ensures an impulse response. With this structure, the model demonstrates high adaptability, interpretability, and reliability in forecasting right-tail VaR.

[3] Author's own calculations in RStudio 2025.07 based on data from https://bank.gov.ua.

Figure 6
Time-series comparison of actual log-returns and ensemble VaR estimates (June 19, 2021 to February 23, 2022)



5. Discussion

The proposed approaches form a new methodology for building adaptive financial strategies based on the integration of risk-oriented indicators into financial planning and the use of advanced models for right-tail VaR estimation. The use of ensemble models—particularly the combination of LSTM, GARCH, XGBoost, and Historical Simulation—enables more accurate and stable forecasts that incorporate both historical and adaptive information.

Forecasting right-tail VaR using the LSTM model showed high sensitivity to changes in market volatility, confirming its effectiveness under unstable conditions. Modeling with LSTM allows for more precise VaR estimates than with traditional methods. Testing results showed that LSTM, especially in short-term forecasting, can be a significant tool for identifying potential financial risks in real time.

Moreover, integrating LSTM into an ensemble model with other methods such as GARCH and XGBoost significantly improves forecast accuracy by combining their strengths: the flexibility of neural networks and the structured volatility analysis of GARCH.

Predicted VaR, particularly in cases of exceedance beyond the acceptable level of right-tail breaches according to backtesting, served as a basis for adjusting funding strategies. Setting borrowing limits or restructuring debt obligations helps reduce the likelihood of major financial losses during periods of high volatility. On the other hand, in cases of stable VaR forecasts, the ensemble model allows for maintaining an optimal risk profile, facilitating financing for investment projects and improving financial resilience through refinancing.

The rolling VaR methodology, applied over a 250-day horizon, enables timely detection of changes in market volatility. This provides the opportunity for rapid adaptation of financial policy, including adjustments to capital structure or changes in loan volumes depending on current volatility. The use of such models is crucial for flexible and risk-sensitive capital management in volatile market conditions.

It is also worth noting that LSTM allows for the integration of dynamic factors, such as changes in lags, which can serve as early indicators of shifts in credit risk. This enables enterprises to apply a proactive approach to budget planning, integrating the best predictive features into financial policy. Thus, VaR not only controls risks but also activates the process of strategic financial decision-making—from liquidity management to long-term capital planning. This interpretation is consistent with recent findings by Zhang et al. [28], who demonstrate that deep neural network–based forecasting of tail-risk measures, including CVaR, significantly improves risk-aware portfolio construction and strategic financial decision-making under uncertainty [28].

These conclusions are supported by findings in several contemporary academic studies. For example, recent research on hybrid ensemble models that combine neural networks (LSTM) with GARCH-type volatility estimators demonstrates significant improvements in VaR forecasting accuracy, enhancing financial resilience under unstable market conditions [12]. Further studies applying deep quantile regression and GAN-based scenario generation confirm the effectiveness of advanced machine learning methods for predicting both VaR and expected shortfall in complex financial environments [25]. Additionally, earlier work on deep learning for financial time series using stacked autoencoders and LSTM [24], as well as LSTM networks for market predictions [15], supports the integration of predictive factors into dynamic budgeting systems, confirming the validity of adaptive methodologies under financial uncertainty. Therefore, the new VaR assessment model not only measures credit risk but also transforms it into a key indicator for strategic management that adapts to market changes. This evolution toward hybrid and data-driven forecasting frameworks is also confirmed by a comprehensive scientometric review by Kehinde et al. [29], which documents a clear shift in the literature from classical econometric models toward machine learning and deep learning approaches in financial market forecasting.

Despite the obtained results, this study has certain limitations. First, the use of data from a single market may restrict the generalizability of the findings; future research should be extended to multinational samples. Second, the ensemble model requires substantial computational resources, which may hinder its real-time application for smaller financial institutions. Third, the impact of macroeconomic shocks and structural breaks were not taken into account in the analysis, which may alter risk dynamics. Promising directions for further research include the integration of macroeconomic predictors, the extension of the forecasting horizon, and the application of explainable AI techniques to enhance the interpretability of results.

6. Conclusions

The feasibility of using a hybrid approach for right-tail VaR estimation under unstable market conditions has been established. Combining traditional (HS, GJR-GARCH), machine learning (XGBoost), and deep neural (LSTM) models provides greater flexibility and adaptability in assessing right-tail risk. Each approach has its strengths—analytical rigor (GARCH), sensitivity to nonlinear dependencies (XGBoost), and the ability to identify complex temporal patterns (LSTM). Integrating these models into an ensemble structure helps mitigate the limitations of each individual methodology and achieve a better balance between accuracy, stability, and responsiveness to market shocks.

The LSTM model proved to be the most effective under conditions of structural instability. It demonstrated the lowest residual volatility ($\hat{\sigma} \approx 0.0137$), high predictive power ($R^2 \approx 0.69$), and accurate right-tail VaR estimation while maintaining a low breach frequency (5.6%). Its advantages—insensitivity to residual distribution assumptions, detection of latent patterns, and adaptability to regime shifts—are critical in a financial environment with high uncertainty. This supports recommending LSTM as a key component in a multi-model forecasting framework.

The ensemble model provided the best compromise between accuracy, stability, and reliability of VaR estimates. The proposed integrated structure, with 40% weight assigned to LSTM and 30% to XGBoost, showed the lowest dispersion of predicted VaR estimates (SD = 1.69), statistical consistency in Kupiec ($p = 0.133$) and Christoffersen ($p = 0.0938$) tests, and the lowest mean excess during breaches (mean_excess ≈ 3.90). As a result, the ensemble effectively scales risk boundaries in response to volatility changes while maintaining high estimation accuracy without excessive conservatism.

The presented approach is practically applicable for strategic financial planning under conditions of high volatility and data scarcity. Even with limited historical data and market instability (up to February 2022), a reliable system for assessing right-tail interest rate risk can be implemented. The proposed models pass statistical forecast validity tests and can be integrated into risk management systems of banks or corporate finance departments. The use of the ensemble model is especially relevant as a flexible and reliable risk management tool in post-crisis or wartime financial environments.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data and scripts that support the findings of this study are openly available in Figshare at https://doi.org/10.6084/m9.figshare.30939428.

Author Contribution Statement

Vitaliy Makohon: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision. **Oleksandra Mandych:** Conceptualization, Validation, Resources, Writing – review & editing, Visualization, Supervision. **Tetiana Staverska:** Methodology, Resources, Data curation, Writing – review & editing, Project administration. **Oleksandr Horokh:** Investigation, Resources, Writing – review & editing, Visualization. **Denys Zabolotny:** Conceptualization, Software, Validation, Investigation, Writing – original draft, Visualization.

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