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COMPARING RISK FORECASTS ON KASE WITH A PRELIMINARY NEWS SENTIMENT ANALYSIS

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ABSTRACT

Purpose of the study – To compare quantitative forecasts of daily KASE index risk and explore whether automatically scored Russian-language news headlines add information beyond news counts. The analysis concerns Kazakhstan only.

Research methodology – Official KASE observations support GARCH, EWMA, LSTM and a quantitative GARCH–LSTM baseline. An exploratory extension compares two otherwise matched hybrids with news counts, with and without sentiment. From 15,536 Kursiv records, 10,669 headlines pass the stated candidate-corpus checks. All forecasts share 495 evaluation dates in 2024–2025. Corpus selection is retrospective and does not establish point-in-time information availability.

Originality (value) of the study – The potential contribution is a context-specific benchmark for KASE: a nonlinear correction to GARCH is evaluated separately from the incremental information in Russian-language headline sentiment beyond news counts. The study documents source records, dated forecasts and corpus-selection limitations. Its contribution is empirical and exploratory.

Research findings – The quantitative hybrid lowers variance RMSE by 0.087% relative to GARCH (Holm-adjusted $p = 0.075$). Adding headline sentiment to the matched news-count control raises variance RMSE by 0.400% (raw two-sided $p = 0.716$; adjusted $p = 1.000$). The sentiment model produces eight 99% VaR exceptions in 495 dates (Kupiec $p = 0.206$). The experiment does not establish a sentiment benefit under the primary variance loss, a 1–3-day warning effect or capital savings.

Keywords: market risk, Value-at-Risk, GARCH, LSTM, NLP, news sentiment, KASE, variance forecasting, chronological evaluation

INTRODUCTION

The Kazakhstan Stock Exchange (KASE) provides the empirical setting for this single-market study. According to KASE's official 2025 results, equity market capitalization reached KZT 39.0 trillion at year-end, while total exchange trading volume across all markets amounted to KZT 400.8 trillion, up 3.0% from 2024 [1]. Total exchange turnover must be distinguished from equity-market turnover and from average daily trading volume.

Forecast-based risk measurement depends on distributional assumptions and on whether estimated dynamics remain adequate outside the fitting sample [2]. VaR itself does not require normally distributed returns or constant correlations: these are assumptions of particular implementations. Engle [3] develops dynamic conditional correlation models, illustrating that econometric risk models can accommodate time-varying dependence. The adequacy of a specific model for KASE therefore requires empirical evaluation.

The 2020–2025 observation period includes the COVID-19 shock, the January 2022 disruption in Kazakhstan and subsequent regional geopolitical shocks. It was selected to encompass changing market conditions rather than a single stable regime. The pandemic context is described in [4]; the January 2022 exchange calendar is documented by KASE [5]. These episodes motivate the study but, because 2020–2023 is the initial training interval, they cannot establish performance in the 2024–2025 holdout period.

This study first asks whether an LSTM correction improves a Student-t GARCH forecast of KASE risk, then explores whether headline sentiment adds information beyond the number of news items. The news extension uses a retrospective corpus and is treated as exploratory rather than as a fully reconstructed historical information set.

The study separates two empirical questions on common target dates: whether a nonlinear correction improves the GARCH benchmark, and whether headline sentiment contributes beyond news counts in otherwise matched hybrid networks. This produces a context-specific assessment of incremental predictive information. Existing hybrid and sentiment-augmented models [6, 7, 8] preclude claiming architectural priority. Source provenance and reproducible forecasts support verification, but do not independently establish scientific novelty.

Chronological evaluation preserves the ordering of observations [9]. Data before 2024 support initialization, training and validation; 2024–2025 is the fixed evaluation interval. GARCH parameters are updated using prior observations. Neural weights remain fixed during evaluation after refitting on the pre-2024 training targets.

Inputs in the quantitative baseline are past KASE returns, squared returns, a rolling mean-square proxy and index-share volume. The hybrid adds past standardized GARCH returns and variance forecasts. The exploratory extension adds headline counts and automatically scored sentiment. Brent and USD/KZT remain excluded pending checks of historical publication availability.

The literature motivates quantitative hybrid modeling and sentiment analysis. The empirical sections distinguish the quantitative baseline from an exploratory news extension, report forecast errors and VaR diagnostics, and document why retrospective corpus limitations constrain interpretation.

Literature Review. VaR summarizes a specified tail quantile of losses over a given horizon. Jorion [2] provides a comprehensive account of its estimation and use in risk management. The Basel Committee's 2006 comprehensive framework [10] documents the historical regulatory treatment of market risk. These sources provide methodological and institutional context, rather than validation of the models evaluated here.

Empirical financial returns can exhibit heavy tails, as documented by Mandelbrot [11]. This motivates checking distributional specifications when estimating tail risk. It does not establish that every parametric VaR model underestimates losses: coverage and independence must be assessed for the fitted model and evaluation sample.

KASE volatility is already represented in the empirical literature. Sabenova et al. [12] compare the KASE index and three energy-related stock-return series over January 2021–January 2023 using conditional volatility models. Their study supplies relevant local context; it does not establish the incremental forecasting value of Russian-language headline sentiment in the matched neural comparison considered here.

The Generalized Autoregressive Conditional Heteroskedasticity framework of Bollerslev [13] extends ARCH dynamics by including lagged conditional variances alongside lagged squared innovations. This parsimonious specification accommodates persistent conditional volatility. Its adequacy for a particular market and forecast horizon remains an empirical question.

Extensions of symmetric GARCH include Nelson's EGARCH [14] and the GJR-GARCH specification of Glosten, Jagannathan and Runkle [15], which allow asymmetric responses to shocks. The asymmetric power framework originates in Ding, Granger and Engle [16]; Ané [17] subsequently analyzes its flexibility. These are relevant alternative benchmarks, but they have not been estimated in the current experiment.

The local setting alone cannot establish novelty. Relative to existing KASE volatility evidence [12], this study focuses on dated out-of-sample forecasts and a matched news-count control. It remains a limited comparison: additional asymmetric econometric benchmarks, repeated neural initializations and verified historical news availability are required for a stronger assessment of model transferability.

Machine learning offers flexible nonlinear specifications, but predictive performance depends on the target, data quality and evaluation design. The IIF–EY public summary of its AI/ML survey [18] provides institutional adoption context; it does not establish forecasting superiority or suitability of a particular architecture for KASE.

Long Short-Term Memory networks [19] were designed to learn temporal dependencies. Their applicability to financial forecasting is an empirical question, and results for one target or market do not establish a general advantage over econometric methods.

Published neural forecasting studies address different targets. Kim and Won [6] combine LSTM with multiple GARCH-type models for stock-index volatility, whereas Fischer and Krauss [20] study stock-return prediction. These results motivate hybrid modeling, but do not provide a directly comparable effect size for KASE. Financial Stability Board discussions [21] also emphasize governance issues that predictive accuracy alone cannot resolve.

Combining econometric forecasts with neural networks is an established research direction. The relevant question for this application is whether the additional model complexity produces measurable gains under a common evaluation protocol.

Kim and Won [6] combine LSTM with GARCH-type models, while Kristjanpoller et al. [7] examine neural–GARCH hybrids in Latin American markets. Léber and Egyed [8], published online in 2025 and assigned to a 2026 volume, explicitly study sentiment-augmented GARCH–LSTM volatility and VaR forecasts for S&P 500 stocks using Bloomberg news and social-media measures. The present study uses a KASE index, public Russian-language headlines and a news-count control. These differences define an empirical application, not a new model class or an exact replication of [8].

Textual analysis in accounting and finance includes dictionaries, document-based measures and predictive applications; Loughran and McDonald [22] review the associated methods and measurement issues. Evidence from particular datasets motivates testing text inputs, but does not establish that a news-sentiment measure will improve KASE variance forecasts.

Loughran and McDonald [23] demonstrate the importance of financial context when constructing textual measures. Araci [24] introduces FinBERT for financial sentiment classification. Classification performance in that work does not validate the different Russian-language checkpoint used in the present experiment or establish its forecasting value.

Language and domain coverage constrain the transfer of sentiment models. Naseem et al. [25] examine Twitter sentiment classification, and Rogers et al. [26] provide an annotated Russian social-media dataset. Neither constitutes validation on Kazakhstan's financial headlines. The checkpoint actually used here is documented separately [27], and its local classification accuracy remains unmeasured.

The candidate empirical contribution is the separation of quantitative nonlinear correction, news intensity and headline sentiment on common KASE forecast dates. The matched control helps interpret incremental sentiment information, but is not itself a new statistical method. Retrospective corpus selection and the lack of local human labels limit the strength of any conclusion about transferability.

Kazakhstan's banking sector is relevant to the application of market-risk models, but aggregate banking indicators are not direct measures of KASE index risk. ARDFM reports banking-sector assets of KZT 61.6 trillion as of 1 January 2025 [28]. The National Bank's Financial Stability Report provides broader systemic-risk context [29].

Currency exposure provides motivation for subsequent extensions. ARDFM reports that foreign-currency deposits represented 22.5% of resident deposits on 1 January 2025, whereas tenge loans represented 91.2% of loans to the economy [28]. These banking indicators are not measures of index risk; USD/KZT has not entered the current executed model comparison.

The sample includes the COVID-19 shock, the January 2022 disruption in Kazakhstan and regional geopolitical shocks. These events motivate careful risk measurement but precede the fixed evaluation interval. The current experiment does not provide prospective crisis-performance evidence for those episodes.

RESEARCH METHODOLOGY

The official KASE archive contains 1,476 dated index levels from 5 January 2020 to 31 December 2025 [30]. These yield 1,475 close-to-close log returns: 980 before 2024 and 495 in 2024–2025. The index-share volume field is measured in millions of tenge and does not represent total exchange turnover. Source dates are retained, including isolated weekend dates; a complete calendar and historical-vintage audit remains outstanding. No synthetic values, interpolation or backward filling are used.

The quantitative baseline uses KASE prices and volume. Separate official histories comprise 2,192 calendar-date USD/KZT rates and 1,518 EIA Brent spot observations; they remain outside model inputs.

A subsequent public-archive query collected 15,536 Russian-language Kursiv records in the Banks and Investments categories, yielding 10,669 candidate headlines after checks [31]. This is a new, single-publisher corpus, not verification of the previously stated 15,847-article dataset.

Table 1 – Descriptive statistics of KASE percentage log returns

Sample	N	Mean	Std dev	Skewness	Excess kurtosis
all	1475	0.0737	0.7147	-0.6437	4.5017
pre 2024	980	0.0580	0.7534	-0.7029	4.9595
test	495	0.1047	0.6306	-0.3596	1.6761

Note – Statistics use all available returns in each indicated interval, without subtracting the later neural initialization window. Standard deviations use n−1; skewness and excess kurtosis use bias-corrected estimators. Excess kurtosis is zero for a Gaussian distribution.

The target is $y_t = r_t^2$, where $r_t = \log(P_t/P_{t-1})$. A zero conditional mean is imposed in all four models, so the conditional second moment is treated as variance. This is a maintained simplification rather than an empirical test of a zero mean. As emphasized in forecast evaluation with imperfect proxies [32], a squared daily return is a noisy variance proxy, not observed latent volatility or high-frequency realized variance. Estimation uses percentage returns for numerical stability; variance outputs are divided by 10,000 before evaluation in decimal-return units.

GARCH(1,1) uses $v_t = \omega + \alpha r_{t-1}^2 + \beta v_{t-1}$ and standardized Student-t innovations. Every forecast is estimated on an expanding history ending strictly before its target date, with at least 252 past returns. All fitted optimizations converged. The EWMA benchmark uses a fixed $\lambda = 0.94$, $v_t = 0.94v_{t-1} + 0.06r_{t-1}^2$, initialized from the mean square of the first 252 returns.

Table 2 – GARCH estimates on 980 pre-2024 returns

Parameter	Estimate	Robust SE	p-value
omega	0.025758	0.024999	0.3029
alpha[1]	0.117593	0.064180	0.06692
beta[1]	0.844229	0.097706	5.595e-18
nu	4.693776	0.677745	—

Note – ω is in squared percentage-return units; its decimal-return value is 0.00000257576. $\alpha + \beta = 0.96182$. $\nu = 4.69378$ is estimated, not fixed at 6.8; no p-value against $\nu = 0$ is interpreted because that null is outside the admissible parameter space. The same-sample BIC values are 2015.080 for Student-t and 2083.945 for Gaussian innovations in the percentage-return scale. Student-t was specified before evaluation; this BIC comparison is supplementary.

Both neural models in the quantitative baseline have two LSTM layers with 128 and 64 units, dropout 0.2, a 32-unit ReLU dense layer and a 20-observation input window. The stand-alone LSTM uses a positive softplus output. Inputs are past percentage returns, their squares, a 20-observation mean square, log(1 + volume) and its first difference. The hybrid also uses past $z_s = r_s/\sqrt{v_s}$ and $\log(v_s)$, based on previously issued GARCH forecasts. Its output is $\hat{v}_t = \hat{v}\text{GARCH}_{,t} \exp(\text{clip}(\delta_t, -3, 3))$; the correction output is initialized at zero. No sentiment or external-market variables enter either baseline network.

Historical GARCH forecasts are constructed sequentially before use as neural features. With 252-return initialization and a subsequent 20-row window, common neural targets begin on 12 February 2021: 462 targets through 2022 and 246 validation targets in 2023. After epoch selection, each network is retrained from scratch on all 708 pre-2024 targets. The test contains all 495 dates from 3 January 2024 to 31 December 2025. Initialization counts and usable targets are therefore distinct from raw index-level counts.

Training uses Adam (learning rate 0.001), chronological batches of 32, MSE, at most 100 epochs, patience 15 and min_delta 10^{-6} on the scaled loss. The target is divided by its training mean. Feature means and standard deviations are estimated from training sequences, including the repetition induced by overlapping windows. Validation uses 2023 only. The selected epoch counts are 50 for LSTM and 1 for the hybrid; final scaling and training then use the 708 pre-2024 targets. Seed 42 and deterministic CPU operations are used. Neural weights

are fixed during 2024–2025; only GARCH parameters are re-estimated daily. No architecture grid search or monthly fine-tuning is claimed.

Variance RMSE, MAE and R^2 compare $\hat{v}_t$ with r_t^2. Separate proxy-scale errors compare $\sqrt{\hat{v}_t}$ with $|r_t|$. QLIKE is recorded as $\log(\hat{v}_t) + r_t^2/\hat{v}_t$, omitting target-only constants. Diebold–Mariano loss comparisons [33] use squared variance errors, a Bartlett HAC estimator with lag 5, the Harvey–Leybourne–Newbold finite-sample correction [34] and two-sided t p-values. Holm correction [35] covers three comparisons against GARCH. Circular block bootstrap [36] uses 2,000 repetitions, block length 20 and common resampled dates across models. Intervals are conditional on the fitted predictions and do not account for retraining or seed variability.

For all four quantitative baseline models, $VaR_{0.99,t} = -q_{0.01,\nu_t}\sqrt{\hat{v}_t}$, where $q_{0.01,\nu} = t_\nu^{-1}(0.01)\sqrt{((\nu-2)/\nu)}$. ν_t is estimated by GARCH on past returns. Applying the same tail family to neural scales is a diagnostic assumption, not separate validation of neural residual distributions. An exception occurs when $-r_t$ exceeds VaR. Kupiec unconditional coverage [37], Christoffersen independence and joint conditional coverage [38] are calculated from dated exceptions and transition counts. Sparse exceptions limit the precision of asymptotic inference.

RESULTS OF THE STUDY

Table 3 – Forecast errors on 495 common evaluation dates

Model	RMSE(v) × 10^4	MAE(v) × 10^4	R^2(v)	RMSE(|r|)
GARCH t	0.744176	0.443206	0.001001	0.00448133
EWMA 0.94	0.746325	0.418951	-0.004777	0.00435731
LSTM	0.759098	0.375822	-0.039464	0.00415183
GARCH–LSTM no NLP	0.743527	0.440396	0.002742	0.00446427

Note – v denotes variance; the final column compares $\sqrt{\hat{v}}$ with |r| in decimal-return units. Scaling the first two columns by 10^4 is for display only. The complete machine-readable table includes MAE on the absolute-return proxy scale and QLIKE.

The quantitative hybrid has the lowest variance RMSE, 0.0000743527, versus 0.0000744176 for GARCH: a relative reduction of 0.087%. LSTM has a 2.005% larger variance RMSE than GARCH but a smaller error against the absolute-return proxy. The nonlinear square-root transformation changes the ranking. Variance R^2 ranges from −0.0395 to 0.0027; these results do not support a claim that the models explain a large fraction of daily squared-return variation.

Table 4 – Comparisons against GARCH under squared variance loss

Model	RMSE gain %	DM statistic	Raw p	Holm p
EWMA 0.94	-0.2888	0.3514	0.7254	0.7254
LSTM	-2.0051	1.0020	0.3168	0.6336
GARCH–LSTM no NLP	0.0872	-2.2476	0.0250	0.0751

Note – developed by the authors based on the research findings.

The hybrid comparison has raw p = 0.0250 but Holm-adjusted p = 0.0751, so superiority is not established at 5% across the tested family. Its unadjusted paired bootstrap 95% interval for RMSE reduction is [0.027%, 0.221%]. This pairwise interval does not incorporate the multiple-comparison adjustment or training uncertainty. Corresponding conditional RMSE intervals in decimal variance units are [0.000053426, 0.000094238] for GARCH and [0.000053315, 0.000094195] for the hybrid.

Table 5 – Diagnostic backtests of one-step 99% VaR

Model	Exceptions	Rate %	Kupiec p	Independence p	Joint p
GARCH t	6	1.212	0.6462	0.0547	0.1421
EWMA 0.94	6	1.212	0.6462	0.0547	0.1421
LSTM	10	2.020	0.0451	0.1878	0.0564

Model	Exceptions	Rate %	Kupiec p	Independence p	Joint p
GARCH–LSTM no NLP	6	1.212	0.6462	0.0547	0.1421

Note – developed by the authors based on the research findings.

Expected exceptions equal 4.95. GARCH, EWMA and the hybrid each produce six exceptions, while LSTM produces ten. Correct unconditional coverage is not rejected for the former three (p = 0.6462) but is rejected for LSTM at the individual 5% level (p = 0.0451). Independence p = 0.0547 for GARCH and the hybrid is close to the threshold; non-rejection does not prove independence. Joint p = 0.1421 also provides no certification of reliability. These are unadjusted diagnostic p-values with few exceptions, not a Basel traffic-light classification.

Exploratory extension using actual news headlines

A fixed public API query retrieved 15,536 unique Russian-language records in Kursiv's Banks and Investments categories over 2020–2025 [31]. The selection is complete for the returned query snapshot, not for all financial media or all historical news. After language, timestamp and same-day duplicate checks, 10,669 candidate headlines remain. Twelve stratified page checks matched the API publication date, but did not establish complete timestamp or text-version accuracy. The raw records, exclusion reasons and source links are preserved.

Candidates require API language ru, langdetect Russian probability at least 0.8, no distinctive Kazakh letters, URL/API date agreement and a modification timestamp between publication and 24 hours afterwards. The later of publication and modification dates receives a two-calendar-day buffer before assignment to a KASE record. Fifteen headlines become eligible after the final 2025 record; 10,654 are assigned to the available calendar. Excluding articles on the basis of later revisions creates retrospective selection: this procedure is not a fully point-in-time backtest. Category coverage also changes sharply across years.

Headlines are scored locally using cointegrated/rubert-tiny-sentiment-balanced, revision e0679dd4460e48648f5d4d819ae0f505384f5a9d, last modified 20 March 2023 [27]. It is a general short-Russian-text classifier, not FinBERT or a newly fine-tuned Kazakh financial model. Following its author's recipe, s = sigmoid(logitpositive) − sigmoid(logitnegative); these sigmoid outputs do not sum to one. No headline exceeded 128 tokens. The automatic labels are 8,422 neutral, 1,423 positive and 824 negative; these are predictions, not manually validated labels or accuracy estimates.

The news index averages eligible headline scores over five KASE records, with exponential decay exp(−0.5 × session age). If the full window is empty, the index is zero. Two channels extend the seven quantitative hybrid inputs: log(1 + new-headline count) and the sentiment index. Both matched networks have nine input channels; the control's sentiment channel is fixed at zero. The same architecture, seed 42, training periods and forecast dates are used. Validation selects one epoch for the count control and five for the sentiment variant. Neural weights remain fixed throughout evaluation.

Table 6 – Matched exploratory news comparison on 495 dates

Model	RMSE(v) × 10^4	R^2(v)	RMSE(|r|)	VaR exceptions	Kupiec p
News count only	0.743598	0.002552	0.00446739	6	0.6462
Count and sentiment	0.746569	-0.005435	0.00411612	8	0.2059

Note – developed by the authors based on the research findings.

Table 7 – Additional loss comparisons in the news experiment

Comparison	RMSE gain %	Raw p	Holm p
Sentiment vs count control	-0.3996	0.7161	1.0000
Sentiment vs no-news hybrid	-0.4091	0.7078	1.0000
Count control vs no-news hybrid	-0.0095	0.2118	0.6353

Note – developed by the authors based on the research findings.

Against the matched count control, sentiment raises variance RMSE by 0.400%. The two-sided loss-comparison p-value is 0.7161, or 1.000 after Holm adjustment over the three additional comparisons. The conditional block-bootstrap 95% interval for improvement is [−1.578%, +1.917%]. Lower error against the absolute-return proxy uses a different scale and does not replace the primary variance-loss conclusion. The sentiment variant has eight VaR exceptions, independence p = 0.1104 and joint-coverage p = 0.1257; these diagnostic non-rejections do not establish reliability.

This extension is exploratory because the 2024–2025 outcomes had already been examined during the quantitative stage. It uses one publisher, one language, one seed and a classifier without local financial gold-standard validation. Retrospective corpus selection and approximate date buffering remain material limitations. The result neither verifies the previously reported NLP gain nor rules out better-specified news models in a future prespecified study.

DISCUSSION

In the quantitative baseline, the observed hybrid improvement is small and not significant after the stated multiple-comparison adjustment. The no-news hybrid and news-count control are selected after only one training epoch, so the learned correction may remain close to its GARCH initialization. This makes repeated seeds and comparison with a simpler calibrated GARCH correction especially important. Robustness across initializations, architectures and rolling neural updates has not been established.

The 2020 and January 2022 episodes belong to initialization or pre-test data, not the 2024–2025 evaluation. No out-of-sample crisis forecasts for those episodes are claimed. The historical trading calendar, vendor revisions and publication times should be audited before treating the exercise as a point-in-time operational backtest. The official retrospective data are genuine, but provenance alone does not resolve these temporal issues.

The exploratory news test detects no improvement under the primary variance loss for this corpus, classifier and training specification. Non-significance does not establish equivalence or the absence of useful sentiment information: the estimated improvement interval spans both signs. A signed average can also cancel opposing headline tones; whether it adequately represents information relevant to variance, rather than return direction, remains an open measurement question. Current-category selection, retrospective exclusion of edited articles, a single publisher and absence of financial sentiment labels limit interpretation. No SHAP ranking, causal news effect or 1–3-day advance-warning result has been established.

An index-level forecast comparison does not estimate portfolio capital requirements, hedging benefits or regulatory acceptance. Any future deployment requires independent validation, portfolio exposures, operational timestamp controls and prospective testing. No percentage capital saving or policy effectiveness is inferred.

CONCLUSIONS

A new experiment on official KASE observations provides a cautious quantitative benchmark. The no-news hybrid improves variance RMSE by 0.087% relative to GARCH, with Holm-adjusted p = 0.075. In an exploratory matched comparison, adding headline sentiment instead increases variance RMSE by 0.400%, with adjusted p = 1.000. Thus the primary error measure does not establish superiority from sentiment in this run. Non-rejection of VaR coverage does not demonstrate overall reliability or crisis protection.

The accompanying package contains authentic source metadata, source hashes, corpus exclusions, sentiment outputs, daily news features, preprocessing and estimation code, neural checkpoints, dated forecasts, training histories and verification checks. The environment uses Python 3.12.14, arch 8.0.0, PyTorch 2.14.0 CPU and transformers 5.17.0; exact dependencies and the language-model revision are recorded. No public repository, previously reported TensorFlow run or author-supplied training corpus is asserted.

The present contribution is a documented KASE benchmark with an exploratory matched sentiment comparison. Its relevance lies in assessing whether an established modeling strategy transfers to this particular setting, while exposing limits of the available evidence. Historical data validation, local sentiment annotation, stronger alternative benchmarks and prespecified evaluation on an untouched period are needed before drawing a robust conclusion about the incremental value of news.

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KASE АЛАҢЫНДАҒЫ ТӘУЕКЕЛ БОЛЖАМДАРЫН САЛЫСТЫРУ ЖӘНЕ ЖАҢАЛЫҚТАР ТОНАЛЬДЫЛЫҒЫН АЛДЫН АЛА БАҒАЛАУ

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АҢДАТПА

Зерттеудің мақсаты — KASE күнделікті тәуекелінің сандық болжамдарын салыстыру және орыс тіліндегі тақырыптардың автоматты бағаланған тональдылығы жаңалықтар санынан бөлек ақпарат бере ме деген сұрақты алдын ала тексеру. Зерттеу Қазақстанмен шектеледі.

Зерттеу әдістемесі — KASE-нің ресми деректері GARCH, EWMA, LSTM және сандық гибрид үшін пайдаланылды. Қосымша жаңалықтар саны бар бірдей гибридті желілер тональдылықпен және онсыз салыстырылды. Kursiv-тің 15 536 жазбасынан 10 669 тақырып іріктелді. Ортақ тест 2024–2025 жылдардағы 495 күнді қамтиды. Корпус ретроспективті жиналды.

Зерттеудің бірегейлігі (құндылығы) — Ықтимал үлес KASE бойынша қолданбалы салыстырудан тұрады: GARCH моделіне сызықтық емес түзету және жаңалықтар санына қосымша орыс тіліндегі тақырыптар тональдылығының ақпараты бөлек бағаланады. Дереккөздер, күні көрсетілген болжамдар және корпус іріктеуінің шектеулері құжатталған. Үлес эмпирикалық әрі алдын ала сипатта; жаңа GARCH–LSTM архитектурасы немесе тексерілген қаржылық тіл жіктеуіші ұсынылмайды.

Зерттеу нәтижелері — Сандық гибрид GARCH-пен салыстырғанда дисперсия RMSE көрсеткішін 0,087%-ға азайтты (Холм түзетуінен кейін p = 0,075). Жаңалықтар санының бақылау нұсқасына тональдылықты қосу дисперсия RMSE көрсеткішін 0,400%-ға арттырды (екіжақты p = 0,716; түзетуден кейін p = 1,000). Тональдылық нұсқасында 495 күнде VaR 99% шегінен сегіз асу болды (Купик тесті p = 0,206). Негізгі метрика бойынша тональдылықтың пайдасы, нарықтан 1–3 күн бұрын белгі беруі және капитал үнемі анықталған жоқ.

Түйін сөздер: нарықтық тәуекел, Value-at-Risk, GARCH, LSTM, NLP, жаңалықтар тональдылығы, KASE, дисперсияны болжау, хронологиялық бағалау

СРАВНЕНИЕ ПРОГНОЗОВ РИСКОВ НА KASE И ПРЕДВАРИТЕЛЬНАЯ ОЦЕНКА ТОНАЛЬНОСТИ НОВОСТЕЙ

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АННОТАЦИЯ

Цель исследования — Сравнить количественные прогнозы дневного риска KASE и предварительно проверить, добавляет ли автоматически оценённая тональность русскоязычных заголовков информацию сверх количества новостей. Исследование ограничено Казахстаном.

Методология исследования — Официальные данные KASE использованы для GARCH, EWMA, LSTM и количественного гибрида. Дополнительно сравнены одинаковые гибридные сети с количеством новостей, с тональностью и без неё. Из 15 536 записей Kursiv отобрано 10 669 заголовков. Общий тест содержит 495 дат 2024–2025 годов. Корпус собран ретроспективно.

Оригинальность (ценность) исследования — Потенциальный вклад состоит в прикладном сравнении на KASE: отдельно оцениваются нелинейная поправка к GARCH и дополнительная информация тональности русскоязычных заголовков сверх количества новостей. Документированы источники,

датированные прогнозы и ограничения отбора корпуса. Вклад носит эмпирический и предварительный характер; новая архитектура GARCH–LSTM и валидированный финансовый языковой классификатор не предлагаются.

Результаты исследования — Количественный гибрид снижает RMSE дисперсии относительно GARCH на 0,087% (p после поправки Холма = 0,075). Добавление тональности к контролю количества новостей увеличивает RMSE дисперсии на 0,400% (двустороннее p = 0,716; после поправки p = 1,000). Вариант с тональностью имеет восемь превышений VaR 99% на 495 датах (p Купика = 0,206). Польза тональности по основной метрике, опережение рынка на 1–3 дня и экономия капитала не установлены.

Ключевые слова: рыночный риск, Value-at-Risk, GARCH, LSTM, NLP, новостная тональность, KASE, прогнозирование дисперсии, хронологическая оценка

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ESG-ФАКТОРЫ И ФИНАНСОВАЯ УСТОЙЧИВОСТЬ КОМПАНИЙ: БИБЛИОМЕТРИЧЕСКИЙ АНАЛИЗ

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АННОТАЦИЯ

Цель исследования заключается в выявлении основных направлений и тенденций развития научных исследований, посвященных влиянию ESG-факторов на финансовую устойчивость компаний.

Методология исследования основана на библиометрическом анализе публикаций, представленных в международной базе данных Scopus за 2016–2026 гг. Для обработки данных использовались программа VOSviewer и пакет Bibliometrix в среде R. В работе применены методы анализа публикационной активности, совместного цитирования, библиографического сопряжения, международного научного сотрудничества и совместной встречаемости ключевых слов.

Оригинальность исследования состоит в комплексном изучении структуры научного поля, связанного с ESG-факторами и финансовой устойчивостью компаний. В отличие от традиционных обзоров литературы, проведенный анализ позволил выявить ключевые тематические направления, научные связи между авторами и странами, а также определить перспективные области дальнейших исследований.

Результаты исследования показали устойчивый рост числа публикаций по тематике ESG после 2019 года. Установлено, что наибольшее внимание исследователей сосредоточено на вопросах устойчивого развития, корпоративного управления, раскрытия ESG-информации, управления рисками и финансовой устойчивости компаний. Анализ тематической структуры показал, что финансовое планирование остается сравнительно новым направлением исследований и обладает потенциалом для дальней-