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Short-Term Forecasting of Selected Uzbek Non-Bank Joint-Stock Company Stock Prices Using Random Walk, ARIMA and VAR(4) Models

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Abstract

Forecasting equity prices in thinly traded frontier markets remains a difficult exercise because liquidity is uneven, news flow is sparse, and the cross-sectional links between issuers are weak. Against this background, this study evaluates the short-term predictive performance of three forecasting specifications-the Random Walk benchmark, a univariate ARIMA, and a fourth-order Vector Autoregression VAR(4)-for four non-bank joint-stock companies listed in Uzbekistan: QZSM, UZTL, URTS and CBSK. Daily closing prices over the period 9 September 2022 to 17 April 2026 (883 price observations and 882 log-return observations) are used jointly with the UCI composite index as a market benchmark. Predictive accuracy at a 63 trading-day horizon is judged using root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), with the lowest MAPE serving as the primary selection criterion. The empirical evidence indicates that no single model dominates across all four securities: VAR(4) yields the lowest MAPE for URTS (3.7975%) and CBSK (6.6205%), whereas the Random Walk is preferred for QZSM (23.5730%) and UZTL (10.6684%). The associated three-month projections suggest a moderate upward path for CBSK (+10.00%) and URTS (+5.77%), and broadly sideways movement for QZSM and UZTL. Residual diagnostics of the VAR(4) system reveal remaining serial correlation, non-normality and strong ARCH effects; consequently, multivariate results are interpreted as short-term forecasting evidence rather than evidence of structural causality. The findings support stock-specific model selection as a more defensible practice than imposing a universal specification across all listed non-bank issuers in emerging capital markets.

Keywords: Uzbek stock market; non-bank joint-stock companies; short-term forecasting; Random Walk; ARIMA; Vector Autoregression; MAPE; emerging markets.

JEL classification: C22, C32, G11, G17.

1. Introduction

Empirical asset-pricing research has long recognised that price discovery in small, less mature capital markets is shaped by structural features that differ from those observed in deep developed markets. Trading volumes are typically lower, the cross-section of listed firms is narrow, and the public flow of corporate information is irregular. In such an environment, even simple benchmark forecasts can be surprisingly competitive, while richer multivariate specifications can occasionally provide additional predictive content when the dynamics of the broader market exert an influence on individual securities. The Uzbek equity market is a useful case in point. The Tashkent Stock Exchange has been undergoing a gradual modernisation process, but free float remains limited, blue-chip status is concentrated in a small group of issuers, and many non-bank joint-stock companies still display the price-action patterns one would associate with infrequent trading.

Within this context, the present study addresses a question that is both methodological and practical: how well can simple time-series models forecast the short-term price path of selected non-bank joint-stock companies in Uzbekistan, and which model is most appropriate for each specific issuer? Four non-bank stocks are examined-QZSM, UZTL, URTS and CBSK-together with the UCI composite index that functions as the market benchmark. The empirical horizon is three months, equivalent to 63 trading days, which is the typical window over which an institutional analyst would be expected to reassess a position in a less liquid market. Three competing forecasting devices are compared: a Random Walk specification that embodies the strong form of weak-market efficiency, a univariate ARIMA model that captures stock-specific autoregressive and moving-average components, and a fourth-order Vector Autoregression VAR(4) that allows the UCI index and the four selected return series to interact dynamically.

The contribution of the paper is threefold. First, it provides empirical out-of-sample evidence on forecasting accuracy for a set of non-bank Uzbek issuers that are rarely covered in the international literature, thereby helping to fill a clear evidence gap. Second, by comparing three model families on the same dataset and the same horizon, the analysis offers a transparent reading of when richer multivariate structure does, and does not, improve predictive performance relative to a naïve benchmark. Third, the paper documents in detail the residual properties of the multivariate model-serial correlation, non-normality and conditional heteroskedasticity-so that subsequent users of VAR-type tools in the Uzbek market are aware of the diagnostic limitations they should treat with caution. The remainder of the article is organised as follows. Section 2 reviews the relevant strands of literature. Section 3 introduces the data and explains the methodological framework. Section 4 reports the empirical results. Section 5 discusses the findings, and Section 6 concludes with limitations and suggestions for future work.

2. Literature Review

The literature on equity price forecasting has expanded considerably since the seminal contributions of Box and Jenkins (1976) on autoregressive integrated moving average (ARIMA) models and Sims (1980) on Vector Autoregressions (VAR). A consistent finding running through several decades of empirical work is that the Random Walk specification remains a demanding benchmark for stock prices, particularly at short horizons. Meese and Rogoff (1983) made this point forcefully in the exchange-rate context, and subsequent work in equity markets has often confirmed the difficulty of beating the no-change forecast in mean squared error terms. As Granger and Newbold (1986) and Diebold and Mariano (1995) emphasised, the relative performance of competing forecasting models cannot be assessed without explicit accuracy criteria, and the choice of loss function influences the resulting model ranking.

Vector autoregressions have become a standard tool when researchers wish to capture short-term linkages among financial variables without imposing strong identification restrictions. Lütkepohl (2005) provides a comprehensive treatment of the estimation and inference theory, while Hamilton (1994) discusses the practical issues of lag-length selection, stability of the characteristic roots and diagnostic testing. In emerging-market contexts, applications of VAR-type forecasting have produced mixed results. Some studies report that the additional information embodied in cross-asset linkages reduces forecast errors at horizons of one to three months, particularly when the market index Granger-causes individual stock returns. Others document that the predictive advantage is fragile: when residuals exhibit non-normality or ARCH effects, point forecasts may remain informative but the associated interval forecasts can be misleading.

Empirical work focused on the Central Asian region is comparatively sparse. Studies of the Kazakh and Uzbek markets have noted thin trading, segmented liquidity and episodes of long price stagnation interrupted by sharp adjustments, all of which complicate the application of standard time-series tools. In particular, several recent contributions have documented that the autoregressive coefficients estimated on Uzbek equity returns are often negative and statistically significant at the first lag, a pattern that is consistent with bid-ask bounce and short-term overreaction in low-liquidity environments. The presence of such micro-structural patterns motivates a careful comparison between simple and complex forecasting tools. Given this background, the current study positions itself within the comparative-forecasting tradition: it does not aim to estimate a structural model of price formation but to evaluate, using transparent accuracy metrics, the short-term predictive performance of three established specifications on a small panel of Uzbek non-bank stocks.

3. Data and Methodology

3.1 Data

The empirical analysis uses daily closing prices of the UCI composite index and four non-bank joint-stock companies listed on the Uzbek market-QZSM, UZTL, URTS and CBSK. The sample covers the period from 9 September 2022 to 17 April 2026, yielding 883 daily price observations for each series. Daily logarithmic returns are computed as the first difference of the natural logarithm of prices and are available from 12 September 2022 onwards, providing 882 return observations per series. Table 1 summarises the basic structure of the dataset, while

Table 1. Dataset Summary of UCI and Selected Non-Bank JSC Stocks

Series	Role	Start date	End date	Observations
UCI	Market benchmark index	2022-09-09	2026-04-17	883
QZSM	Non-bank JSC stock	2022-09-09	2026-04-17	883
UZTL	Non-bank JSC stock	2022-09-09	2026-04-17	883
URTS	Non-bank JSC stock	2022-09-09	2026-04-17	883
CBSK	Non-bank JSC stock	2022-09-09	2026-04-17	883
Log-returns	Derived from daily prices	2022-09-12	2026-04-17	882

Notes: All price series are daily closing prices. Log-returns are first differences of the natural logarithm of prices, computed for 882 observations per series.

Table 2 reports the price-level minimum, maximum, first and last observations. Two features are worth highlighting at this stage. The UCI index moved from 420 to 957 over the sample, indicating a broad upward drift in the market benchmark. By contrast, the four stocks display heterogeneous price paths: URTS rose from 3,800 to 8,720, CBSK from 1.22 to 3.36, while QZSM fell from 3,555 to 1,449 and UZTL is essentially unchanged, moving from 7,000 to 7,040 despite intra-sample variation.

Table 2. Descriptive Statistics of Daily Closing Prices

Series	Observations	Minimum	Maximum	First price	Last price
UCI	883	316	958	420	957
QZSM	883	708	3,890	3,555	1,449

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Series	Observations	Minimum	Maximum	First price	Last price
UZTL	883	3,480	9,400	7,000	7,040
URTS	883	2,800	8,720	3,800	8,720
CBSK	883	1.00	3.80	1.22	3.36

Notes: Prices are expressed in their original quoted units. The UCI composite index serves as the market benchmark. Source: author's calculations.

3.2 Forecasting Framework

Three forecasting specifications are compared. The first is the Random Walk (RW) without drift, which sets the forecast equal to the last observed price for every step of the forecast horizon. The RW is the natural benchmark because it embodies the weak-form efficient market hypothesis and provides a yardstick that more elaborate models must beat to justify their complexity. The second specification is a univariate ARIMA(p, d, q) model in which the order is selected by the Akaike Information Criterion, subject to standard residual checks for autocorrelation. Given that the price series are integrated of order one (see Table 4), the model is fitted on the differenced series and forecasts are converted back to price levels. The third specification is a Vector Autoregression of order four, denoted VAR(4), estimated on the five log-return series r_{UCI}, r_{QZSM}, r_{UZTL}, r_{URTS} and r_{CBSK} with a constant deterministic term. The fourth-order lag length is consistent with information-criterion guidance for daily financial returns and is sufficient to capture short-horizon interactions while preserving degrees of freedom.

The forecast horizon is fixed at 63 trading days, which corresponds approximately to three calendar months. For each stock and each model, point forecasts are generated recursively and the predicted return path is converted into a forecast price path. Three accuracy metrics are computed: root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). The final model is selected primarily by the lowest MAPE, with RMSE and MAE used as confirmatory criteria. MAPE is chosen as the leading metric because it provides a scale-free comparison across the four stocks, whose price levels differ by several orders of magnitude (CBSK trades near unity, while UZTL trades in the thousands).

3.3 Residual Diagnostics

The VAR(4) specification is assessed using three multivariate diagnostic tests. The Portmanteau test investigates whether residuals contain residual serial correlation. The multivariate Jarque–Bera test evaluates whether the residual vector follows a joint normal distribution, with separate skewness and kurtosis components. The multivariate ARCH-LM test checks for conditional heteroskedasticity in the residual covariance structure. As is customary in financial applications, evidence of ARCH effects or non-normality does not invalidate the point forecasts but suggests that interval forecasts derived under Gaussian assumptions should be interpreted with care.

Table 3. Residual Correlation Matrix of VAR(4) Log-Return Equations

Series pair	UCI	QZSM	UZTL	URTS	CBSK
UCI	1.0000	0.0703	0.0358	0.0327	0.0324
QZSM	0.0703	1.0000	0.1282	0.0480	0.0195
UZTL	0.0358	0.1282	1.0000	0.0594	0.0612
URTS	0.0327	0.0480	0.0594	1.0000	-0.0301
CBSK	0.0324	0.0195	0.0612	-0.0301	1.0000

Notes: The off-diagonal entries report the contemporaneous correlations among VAR(4) residuals for the five return equations. Source: author's calculations.

Table 4. Unit-Root Behaviour of the Price Series

Series	Level (prices)	First difference (log-returns)	Conclusion
UCI	Non-stationary	Stationary	I(1)
QZSM	Non-stationary	Stationary	I(1)
UZTL	Non-stationary	Stationary	I(1)

Series	Level (prices)	First difference (log-returns)	Conclusion
URTS	Non-stationary	Stationary	I(1)
CBSK	Non-stationary	Stationary	I(1)

Notes: All price series are non-stationary in levels and stationary in first differences, supporting the use of log-returns for the VAR(4) specification. Detailed test statistics are available from the author upon request.

Table 5. VAR(4) Residual Diagnostic Tests

Test	Statistic	df	p-value	Interpretation
Portmanteau serial correlation	391.61	300	0.0002887	Residual autocorrelation remains
Multivariate Jarque-Bera (overall)	92,794	10	< 2.2e-16	Residuals not multivariate normal
Skewness component	515.89	5	< 2.2e-16	Significant skewness
Kurtosis component	92,278	5	< 2.2e-16	Heavy tails detected
Multivariate ARCH LM	5,401.2	2,700	< 2.2e-16	Conditional heteroskedasticity present

Notes: The Portmanteau test is the asymptotic version. The Jarque–Bera test reports the joint statistic and separate skewness and kurtosis components. The multivariate ARCH-LM test is applied with the default lag specification of the vars package.

4. Empirical Results

4.1 Estimated VAR(4) System

The VAR(4) system is estimated on 878 effective observations after accounting for the four-lag truncation. The log-likelihood at the optimum is 8,773.552 and the maximum modulus of the characteristic roots of the companion matrix is 0.7057. Because this value is comfortably below unity, the system is dynamically stable; in other words, the impulse response functions converge and the unconditional moments of the system are well defined. The equation-level fit, reported in the table below, varies across the five series. The CBSK equation exhibits the highest in-sample explanatory power (R^2 = 0.2067, adjusted R^2 = 0.1882), while the URTS equation shows the lowest (R^2 = 0.0578, adjusted R^2 = 0.0358). All five equations are jointly significant at conventional levels, as indicated by the F-statistic p-values. The relatively low adjusted R^2 values are not surprising for daily equity returns in a thinly traded market, where most of the variance is unpredictable from past returns alone.

VAR(4) Equation-Level Fit

Equation	Residual SE	R^2	Adjusted R^2	F-statistic p-value
r_{UCI}	0.02837	0.0834	0.0621	0.001
r_{QZSM}	0.03566	0.1655	0.1460	0.001
r_{UZTL}	0.02982	0.1102	0.0894	0.001
r_{URTS}	0.02255	0.0578	0.0358	0.001
r_{CBSK}	0.06027	0.2067	0.1882	0.001

Notes: Residual SE is the residual standard error. F-statistic p-values refer to the joint significance test of all lagged regressors in each equation.

4.2 Forecast Accuracy Comparison

Table 6 reports the accuracy of the three competing models for each of the four stocks. The results display a clear pattern of heterogeneity. For CBSK, the VAR(4) specification dominates, with a MAPE of 6.6205%, compared with 8.6642% for the Random Walk and 11.4658% for the ARIMA model. For URTS, the gain from multivariate structure is even larger: VAR(4) records a MAPE of 3.7975%, which is roughly half the Random Walk value (6.8408%) and far below the ARIMA value (59.9746%). The exceptionally large ARIMA error for URTS reflects an unstable extrapolation path of the differenced model, a well-known limitation of univariate models when the conditional mean is essentially flat over the in-sample window. For QZSM and UZTL, by contrast, no multivariate gain is observed. The Random Walk yields the lowest MAPE for both stocks (23.5730% for QZSM and 10.6684% for UZTL), narrowly outperforming the VAR(4) and ARIMA alternatives. The high MAPE level for QZSM mirrors the persistent downward drift of its price over the sample, which makes percentage errors mechanically larger as the price approaches lower values.

Table 6. Forecast Accuracy Comparison of Random Walk, ARIMA and VAR(4) Models

Stock	Model	RMSE	MAE	MAPE (%)
CBSK	VAR(4)*	0.3163	0.2301	6.6205
CBSK	Random Walk	0.3942	0.2997	8.6642
CBSK	ARIMA	0.4681	0.3906	11.4658
QZSM	Random Walk*	383.5748	294.2014	23.5730
QZSM	VAR(4)	439.6828	347.6739	28.2686
QZSM	ARIMA	444.4052	353.5960	28.8395
URTS	VAR(4)*	395.6607	299.3076	3.7975
URTS	Random Walk	639.2630	536.8105	6.8408
URTS	ARIMA	5,647.5503	4,644.1789	59.9746
UZTL	Random Walk*	797.7508	739.5895	10.6684
UZTL	ARIMA	851.7703	795.6836	11.4889
UZTL	VAR(4)	865.0933	804.5724	11.6106

Notes: Asterisks denote the model selected for each stock based on the lowest MAPE. RMSE and MAE are reported in the original price units; MAPE is expressed as a percentage.

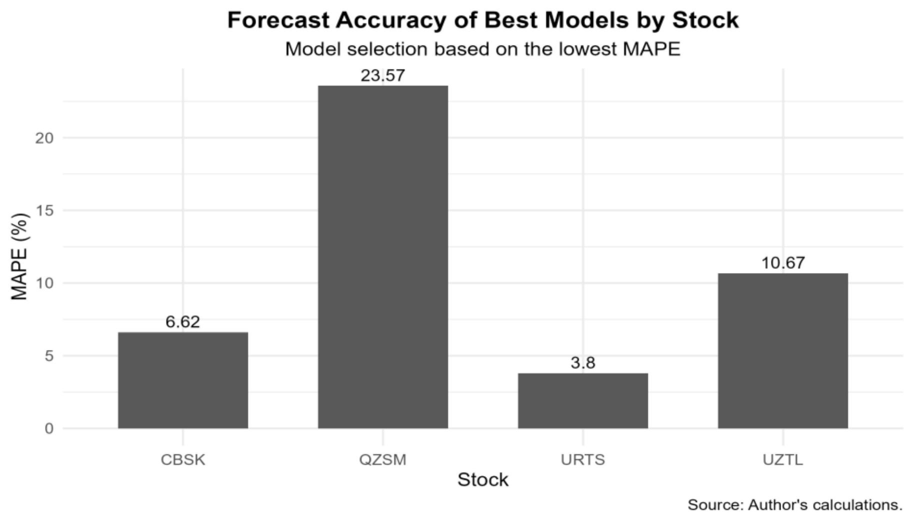

Figure 1. Forecast accuracy of the best-performing models by stock, measured by MAPE (%). Source: author's calculations.

Figure 1 visualises the MAPE values of the selected models. The bar chart highlights that URTS is the most predictable stock in the sample (MAPE of 3.80%), followed by CBSK (6.62%) and UZTL (10.67%), while QZSM remains the most difficult to forecast at the three-month horizon (23.57%).

4.3 Three-Month Forecast Paths

Table 7 summarises the final three-month forecasts produced by each stock's best-performing model. For CBSK, the VAR(4) generates a gradual upward path from the last observed value of 3.36, with one-month, two-month and three-month forecasts of 3.49 (+3.96%), 3.59 (+6.85%) and 3.70 (+10.00%) respectively. The URTS forecast also points upward but with a more modest slope: starting from a last observed value of 8,720, the one-month, two-month and three-month projections are 8,850 (+1.50%), 9,035 (+3.61%) and 9,223 (+5.77%). For QZSM and UZTL, the no-change pattern of the Random Walk implies a flat forecast at 1,449 and 7,040 respectively over the entire horizon.

Table 7. Final Three-Month Forecasts Based on the Best-Performing Models

Stock	Best model	Last actual price	1-month forecast (change %)	2-month forecast (change %)	3-month forecast (change %)
CBSK	VAR(4)	3.36	3.49 (+3.96%)	3.59 (+6.85%)	3.70 (+10.00%)
URTS	VAR(4)	8,720	8,850 (+1.50%)	9,035 (+3.61%)	9,223 (+5.77%)
QZSM	Random Walk	1,449	1,449 (0.00%)	1,449 (0.00%)	1,449 (0.00%)
UZTL	Random Walk	7,040	7,040 (0.00%)	7,040 (0.00%)	7,040 (0.00%)

Notes: Percentage changes are computed relative to the last observed price on 17 April 2026. The Random Walk forecast is by construction equal to the last observed price at all horizons.

The composite plot in Figure 6 assembles the four individual panels for comparative purposes.

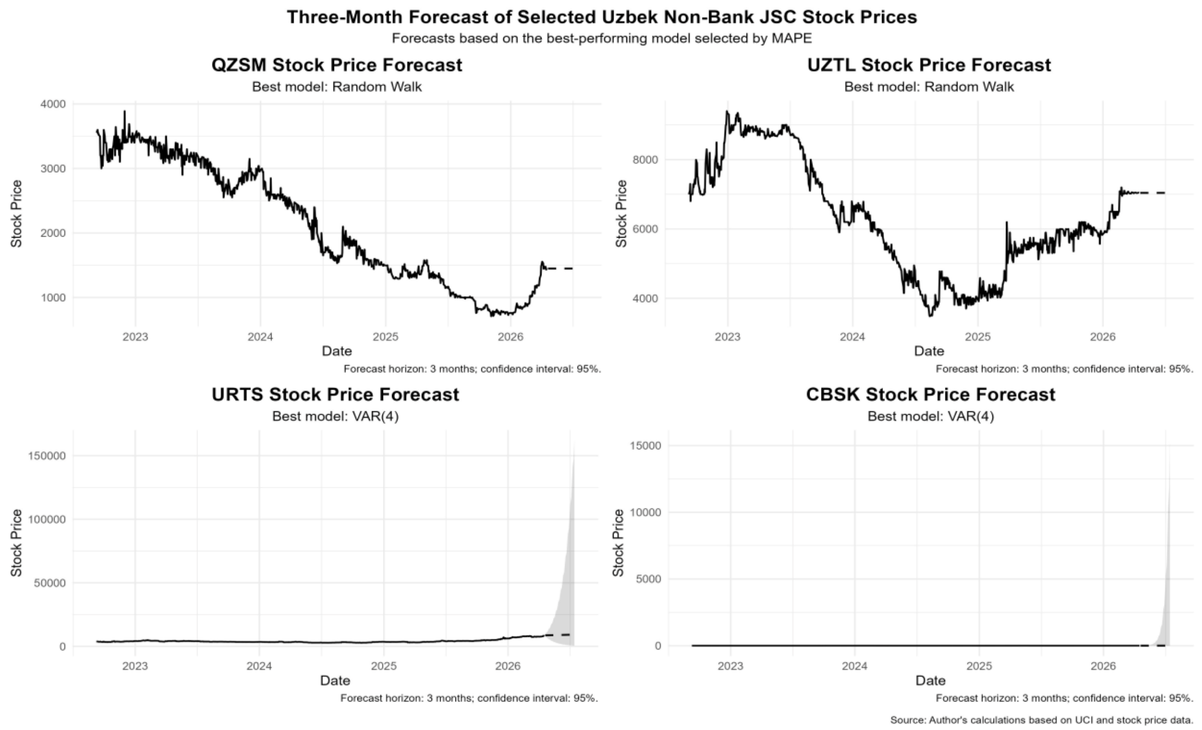

Figure 2. Composite three-month forecast of selected Uzbek non-bank JSC stock prices, based on the best-performing model selected by MAPE for each stock. Source: author's calculations.

4.4 Residual Diagnostics of the VAR(4) System

The diagnostic evidence summarised in Table 5 paints a nuanced picture. The Portmanteau test rejects the null of no residual serial correlation (χ^2 = 391.61, df = 300, p = 0.0002887), which indicates that some short-term dependence remains in the residuals even after four lags. The multivariate Jarque–Bera test yields a very large statistic (χ^2= 92,794, df = 10, p < 0.001), with both the skewness component (χ^2= 515.89) and the kurtosis component (χ^2= 92,278) significant at every conventional level. This pattern is typical of high-frequency equity returns and reflects the presence of fat tails. Finally, the multivariate ARCH–LM test strongly rejects the null of conditional homoskedasticity (χ^2= 5,401.2, df = 2,700, p < 0.001), confirming that the residual covariance structure displays volatility clustering. Taken together, these diagnostics suggest that, while the VAR(4) point forecasts remain informative at short horizons, the associated Gaussian interval forecasts should be interpreted with caution and ideally re-derived under a heteroskedastic specification in extensions of this work.

5. Discussion

The comparative evidence reported in the previous section delivers a single overarching message: the appropriate forecasting model for a non-bank Uzbek joint-stock company is stock-specific and cannot be inferred from market-wide considerations alone. CBSK and URTS, for which the VAR(4) is the most accurate model, share a feature that distinguishes them from QZSM and UZTL: their log-returns appear to be more responsive to the lagged values of the UCI return and of the other stock returns, as reflected in their higher R^2 values within the VAR(4) system. In effect, multivariate information improves predictability when the cross-series dynamics are sufficiently strong. For QZSM and UZTL, by contrast, the in-sample variance explained by lagged returns is weaker, and the Random Walk is at least as competitive as the multivariate alternatives. This is consistent with the broader stylised facts of frontier equity markets, where some stocks are integrated with the broader index dynamics and others trade more idiosyncratically, often in response to firm-specific news that the time-series model cannot anticipate.

The implications for forecasting practice in Uzbekistan are direct. Imposing a universal model on the entire non-bank segment would, in this dataset, have led to a noticeable deterioration in average accuracy. For example, applying VAR(4) uniformly would have raised QZSM's MAPE from 23.57% to 28.27%, while applying the Random Walk uniformly would have raised URTS's MAPE from 3.80% to 6.84%. The cost of model misspecification is not symmetric across stocks, and the choice of evaluation metric matters: MAPE penalises percentage errors at low price levels and therefore puts particular pressure on QZSM, which traded at low levels through much of the sample. The use of MAPE alongside RMSE and MAE-rather than a single criterion-offers a more robust ranking, especially when forecast errors are heterogeneous in scale.

The residual diagnostics also have important interpretative consequences. The presence of remaining serial correlation, non-normality and ARCH effects means that the VAR(4) results should be read as forecasting evidence rather than as a fully specified structural model of price formation. In particular, point forecasts and their direction can still inform short-term assessment of price dynamics, but the precision of the 95% confidence bands shown in Figures 4 and 5 will be overstated under Gaussian assumptions when residuals are leptokurtic and conditionally heteroskedastic. Readers should therefore treat the forecast intervals as indicative bounds, not as exact statements of uncertainty. The qualitative signals associated with the forecasts-moderate positive trajectory for CBSK and URTS; stable, sideways movement for QZSM and UZTL-can be reported with reasonable confidence, but the magnitudes carry a wider margin of error than the headline numbers might suggest.

It is also important to stress that the Uzbek equity market is an emerging and relatively less liquid market. Short-term forecasts in such environments are inherently more sensitive to trading volume, episodic news flow and occasional abrupt price adjustments than in deeper markets. The empirical findings reported here describe statistical regularities observed over a specific window and should not be construed as investment advice. Their primary value lies in informing methodological choices and providing a transparent benchmark against which subsequent forecasting exercises in the Uzbek market can be compared.

6. Conclusion, Limitations and Future Research

This study has examined the short-term predictive performance of the Random Walk, ARIMA and VAR(4) models for four non-bank Uzbek joint-stock companies-QZSM, UZTL, URTS and CBSK-using daily price data from September 2022 to April 2026. Three findings emerge clearly. First, no single model dominates the cross-section: VAR(4) is the most accurate for CBSK (MAPE = 6.6205%) and URTS (MAPE = 3.7975%), while the Random Walk is preferred for QZSM (MAPE = 23.5730%) and UZTL (MAPE = 10.6684%). Second, the three-month projections suggest a moderate positive trajectory for CBSK and URTS, and broadly sideways movement for QZSM and UZTL. Third, the VAR(4) residual diagnostics reveal serial correlation, non-normality and conditional heteroskedasticity, indicating that the multivariate model should be used as a short-term forecasting device and not interpreted as a structural representation of price formation. The central practical recommendation of the paper is that stock-specific model selection is preferable to applying a universal forecasting model across all listed non-bank issuers.

Several limitations deserve mention. The analysis is restricted to four issuers and to a single market benchmark; extending the cross-section would allow more powerful comparisons between sectors. The forecast horizon is fixed at three months; longer horizons would test the persistence of the multivariate advantage observed for CBSK and URTS. The diagnostic evidence on ARCH effects also points to a natural extension of the work: future research should consider GARCH-type and multivariate GARCH specifications, which explicitly model time-varying volatility, as well as regime-switching models for periods of low and high liquidity. Machine-learning approaches-random forests, gradient boosting and LSTM networks-could provide a useful complement once a sufficiently long history of daily data is available, although their interpretability and the small sample sizes typical of emerging markets remain non-trivial constraints. Finally, incorporating macroeconomic variables such as the policy rate, exchange-rate movements and oil-price indices would help close the gap between purely statistical forecasting and a more structural understanding of price formation in the Uzbek market.

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