World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

SHORT-TERM FORECASTING OF BANK STOCK PRICES IN AN EMERGING FRONTIER MARKET: EVIDENCE FROM RANDOM WALK, ARIMA AND VAR MODELS IN UZBEKISTAN

Sindarov Fazliddin Kakhramanovich
Junior Researcher Research Center For Scientific Foundations and
Issues of Economic Development of Uzbekistan Under The Tashkent State University of Economics,
Senior lecturer at the International Islamic Academy of Uzbekistan, Tashkent, Uzbekistan
Author e-mail: f.sindarov@tsue.uz, fazliddinst2020@gmail.com

Article history:
Received: 8th March 2026
Accepted: 7th April 2026

Abstract:
This study examines the short-term forecasting dynamics of bank stocks listed on the Republican Stock Exchange "Toshkent" using daily data from 9 September 2022 to 17 April 2026 (883 price observations; 882 logarithmic returns). Four banking issuers – HMKB, SQB, IPKY and ALKB – are analysed jointly with the Uzbekistan Composite Index (UCI) within a unified empirical framework that combines benchmark Random Walk, univariate ARIMA and multivariate VAR(4) models. The Augmented Dickey–Fuller test confirms stationarity of all return series, while ARCH–LM tests reveal pronounced volatility clustering in UCI, HMKB, SQB and ALKB. Annualised volatility ranges from 60.41% (SQB) to 153.41% (IPKY), evidencing substantial heterogeneity in idiosyncratic risk. The VAR(4) system is stable (maximum modulus of characteristic roots 0.6377), and forecast error variance decomposition reveals strong own-shock dominance ranging from 94.79% to 98.00% at the 20-day horizon, while Granger causality tests indicate that bank-specific shocks rather than the aggregate index drive system dynamics. Out-of-sample comparisons based on RMSE, MAE and MAPE select VAR(4) for ALKB, HMKB and IPKY, and ARIMA for SQB. The findings document weak cross-asset information transmission, persistent volatility clustering and heterogeneous predictability – stylised facts characteristic of frontier equity markets – and provide direct policy guidance for ongoing capital-market reforms in Uzbekistan.

Keywords: Bank stock forecasting; ARIMA; VAR; emerging frontier markets; Uzbekistan Composite Index; volatility clustering; market microstructure.

JEL classification: C32; C53; G14; G17; G21.

1. INTRODUCTION

The forecasting of equity prices remains one of the most enduring challenges in financial econometrics. Since Fama (1970) formalised the Efficient Market Hypothesis (EMH), an enormous body of theoretical and empirical work has investigated whether stock returns are predictable, under what informational conditions, and with what economic magnitude. The literature has matured into a refined consensus: in deep, liquid and informationally efficient markets, short-term returns approximate a martingale and are therefore unconditionally difficult to forecast (Fama, 1991; Campbell, Lo and MacKinlay, 1997; Lo and MacKinlay, 1999). In thinner, more segmented and less informationally rich markets, however, return processes deviate systematically from the martingale benchmark – producing persistent autocorrelations, volatility clustering, and weak cross-asset information transmission that, in principle, leave space for econometric forecasting models to outperform the random walk.

Frontier equity markets sit firmly in this second category. According to Berger, Pukthuanthong and Yang (2011) and Speidell (2011), frontier markets are characterised by limited liquidity, fragmented price discovery, restricted institutional investor participation, and informational asymmetries that distinguish them from both developed and conventional emerging markets. In such environments, short-term forecasting models that exploit autocorrelation structures, lagged cross-stock dynamics and volatility clustering are not merely academic exercises: they offer concrete value

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

for investors, regulators and exchange operators seeking to understand the mechanics of price formation in evolving capital markets.

This paper contributes to that literature by providing an integrated short-term forecasting analysis of bank stocks listed on the Republican Stock Exchange "Toshkent" (UZSE), the principal equity venue of the Republic of Uzbekistan. The Uzbek capital market constitutes a particularly interesting laboratory. Founded in 1994 and modernised in 2016 through cooperation with the Korea Exchange, UZSE has, since 2018, undergone an accelerated reform programme. Total trading volume reached approximately USD 2 billion in 2024, a 7.5-fold increase relative to 2023, and aggregate market capitalisation peaked at USD 23.7 billion in December 2025 (U.S. Department of State, 2025; CEIC Data, 2026). Banking-sector privatisation has emerged as a structural pillar of the reform: in June 2023, OTP Bank acquired a 73.71% stake in Ipoteka-Bank, completing the first foreign privatisation in the Uzbek banking-privatisation programme; the Asian Development Bank, the European Bank for Reconstruction and Development, and the International Finance Corporation have provided convertible-loan facilities to Sanoat Qurilish Bank to support its forthcoming privatisation; and the National Investment Fund (UzNIF) launched a dual London–Tashkent IPO in April 2026 (Asian Development Bank, 2023; OTP Group, 2023; Spot.uz, 2026). These developments place the question of how Uzbek bank-stock prices are formed at the centre of an active policy debate.

Despite this policy salience, peer-reviewed econometric evidence on UZSE-listed equities is scarce. Eshov et al. (2021) provide the only widely cited prior empirical study, applying a structural-equation model to assess the impact of COVID-19 on the Uzbek market. To the best of our knowledge, no published study has yet examined the time-series dynamics, volatility properties, or forecasting performance of competing model classes for Uzbek bank stocks. This paper fills that gap by jointly analysing four listed bank issuers – Hamkorbank (HMKB), Sanoat Qurilish Bank (SQB), IPAK YO'LI Bank (IPKY) and Aloqabank (ALKB) – alongside the Uzbekistan Composite Index (UCI) over the period 9 September 2022 to 17 April 2026. The dataset comprises 883 daily price observations and 882 logarithmic returns.

The empirical strategy proceeds in five sequential steps. First, we establish the time-series properties of all return series via Augmented Dickey–Fuller (Dickey and Fuller, 1979) unit-root tests and Engle's (1982) ARCH–LM heteroscedasticity tests. Second, we quantify return-risk heterogeneity through annualised and 30-day rolling volatility measures. Third, we benchmark a naive Random Walk forecasting model against univariate ARIMA models (Box, Jenkins, Reinsel and Ljung, 2015) and a multivariate VAR(4) system selected via the Akaike Information Criterion and Final Prediction Error criterion (Sims, 1980; Lütkepohl, 2005). Fourth, we evaluate the VAR(4) model through stability analysis, residual diagnostics, Granger (1969) causality tests, generalised impulse response functions and forecast error variance decomposition. Fifth, out-of-sample forecast accuracy is assessed using an 80/20 train–test split with the RMSE, MAE and MAPE loss functions, with the lowest MAPE adopted as the primary selection criterion (Hyndman and Koehler, 2006; Hyndman and Athanasopoulos, 2021).

Five principal findings emerge. First, all log-return series are stationary and exhibit pronounced volatility clustering, with the exception of IPKY where the ARCH–LM test fails to reject the null. Second, return distributions are markedly heterogeneous: annualised volatility ranges from 60.41% for SQB to 153.41% for IPKY. Third, the VAR(4) system is stable, with maximum characteristic root 0.6377, but its residuals fail standard tests of serial correlation, normality and conditional homoscedasticity – limitations that are explicitly acknowledged. Fourth, forecast error variance decomposition reveals own-shock dominance between 94.79% and 98.00% at the 20-day horizon, indicating that the Uzbek bank-stock market remains segmented and that cross-asset information transmission is weak. Fifth, the multivariate VAR(4) model outperforms both the Random Walk benchmark and univariate ARIMA models for ALKB, HMKB and IPKY, while ARIMA proves preferable for SQB. The 3-month projected price changes range from approximately +0.04% (ALKB) and +12.49% (HMKB) to +15.04% (IPKY) and +56.63% (SQB), with the magnitude of SQB's forecast warranting interpretive caution.

The contribution of this study to the literature is fivefold. First, it provides one of the first systematic empirical applications of competing forecasting frameworks to listed bank stocks in Uzbekistan's capital market. Second, it integrates benchmark, univariate and multivariate forecasting techniques within a unified comparative design. Third, it embeds the forecasting analysis in a comprehensive diagnostic apparatus encompassing stationarity testing, ARCH–LM heteroscedasticity tests, multivariate residual diagnostics, Granger causality, impulse responses and variance decomposition. Fourth, it employs three complementary forecast-accuracy metrics and selects

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

the optimal model bank-by-bank rather than imposing a uniform specification. Fifth, by documenting weak information transmission, persistent volatility clustering and heterogeneous predictability, the paper enriches the broader literature on frontier equity markets where liquidity, market depth and informational efficiency remain structurally limited.

The remainder of the paper is organised as follows. Section 2 surveys the relevant theoretical and empirical literature. Section 3 describes the data, variable construction and methodological framework. Section 4 reports the empirical results. Section 5 discusses the economic and policy implications of the findings. Section 6 presents the conclusion. Section 7 acknowledges the limitations of the study and outlines avenues for further research. References follow.

2. LITERATURE REVIEW

This section organises the relevant literature into eight thematic strands that jointly motivate the methodological design of the study. Each strand corresponds to a specific empirical step in the analysis.

2.1. The Efficient Market Hypothesis and the Limits of Stock Price Prediction

The theoretical baseline for any stock-price forecasting study is the Efficient Market Hypothesis. Fama (1970) classified market efficiency into weak, semi-strong and strong forms, with the weak form positing that current prices reflect all information embedded in past prices. Under weak-form efficiency, returns are unconditionally unpredictable using past prices alone. Fama (1991) subsequently re-cast weak-form tests as "tests of return predictability" and acknowledged that returns are partially predictable from past returns, dividend yields and term-structure variables – leaving open a meaningful empirical question concerning the magnitude and economic relevance of any predictability. Grossman and Stiglitz (1980) provide the theoretical resolution: perfect informational efficiency is logically incompatible with costly information acquisition, so equilibrium markets must exhibit a degree of predictability sufficient to compensate informed traders. This insight is particularly germane to frontier markets where information costs are high, institutional sophistication is uneven, and price discovery is incomplete.

2.2. The Random Walk Hypothesis and Its Tests

The corollary of weak-form efficiency is the Random Walk Hypothesis, originally articulated by Bachelier (1900) and formally restated by Samuelson (1965), who demonstrated that properly anticipated prices fluctuate randomly. Lo and MacKinlay (1988) developed the variance-ratio test, which exploits the property that under a random walk the variance of k-period returns is k times the variance of one-period returns. They reject the random-walk null for U.S. weekly stock returns. Subsequent multiple variance-ratio tests by Chow and Denning (1993) and applications to emerging markets by Hoque, Kim and Pyun (2007) generally find weak rejection of the random-walk null in mature markets and stronger evidence of return autocorrelation in less developed venues. Lo and MacKinlay (1999) consolidate the broader empirical case against simple random-walk dynamics. The Random Walk model nevertheless retains an important role in applied work as a forecasting benchmark: any candidate model must demonstrate out-of-sample superiority over the naive "no-change" forecast to be considered economically relevant (Hyndman and Athanasopoulos, 2021).

2.3. ARIMA Models in Stock-Price Forecasting

Within the univariate time-series tradition, the autoregressive integrated moving average (ARIMA) framework of Box and Jenkins (1970), updated through Box, Jenkins, Reinsel and Ljung (2015), provides a flexible and parsimonious specification capable of accommodating a wide range of dependence structures. ARIMA models combine autoregressive (AR) terms that capture persistence, moving-average (MA) terms that capture short-run dynamics, and integration orders that ensure stationarity. Adebiyi, Adewumi and Ayo (2014) provide a widely cited application to Nigerian and U.S. stocks (including a Zenith Bank ARIMA(1,0,1) example) and show that ARIMA forecasts can be competitive with neural-network alternatives at short horizons. Reddy (2019) and Dikshit and Singh (2019) extend ARIMA forecasting to Indian National Stock Exchange data, while Chowdhury and Islam (2021) demonstrate the model's usefulness for thinly traded Bangladeshi equities. In the banking-sector context, Shogole et al. (2024) compare ARIMA and GARCH(1,1)–ARMA(2,2) forecasts for Standard Bank in South Africa and select the volatility-augmented specification on AIC criteria. The general conclusion of this strand is that ARIMA models perform well at short horizons in low-to-moderately liquid markets, while their performance deteriorates relative to multivariate alternatives when meaningful cross-asset dynamics are present.

2.4. Vector Autoregression and Dynamic Interdependence

The vector autoregressive (VAR) framework introduced by Sims (1980) provides a natural multivariate extension. A VAR(p) treats each variable as

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

a linear function of its own lags and the lags of all other system variables, with no a priori exogeneity restrictions. Lütkepohl (2005) furnishes the standard graduate-textbook treatment, including lag-length selection criteria, stability conditions, residual diagnostics, impulse-response analysis and forecast error variance decomposition. Stock and Watson (2001) provide an accessible methodological summary, while Pesaran and Shin (1998) introduce the generalised impulse response function (GIRF), which is invariant to the ordering of variables in a Cholesky decomposition. Diebold and Yilmaz (2009, 2012) build on the GIRF to construct spillover indices that quantify directional information transmission across markets and assets. In the emerging-market context, Bhowmik et al. (2022) apply VAR plus Granger causality plus GARCH-M jointly across six Asian markets to study crisis-period reactions, while Nguyen et al. (2022) document substantial sectoral volatility spillovers in Vietnam. The applicability of VAR to bank-stock systems specifically rests on the proposition that bank prices are influenced by both market-wide news (captured by index returns) and idiosyncratic, possibly cross-bank, dynamics.

2.5. Volatility Clustering and the ARCH/GARCH Family

A robust stylised fact of financial returns is volatility clustering: large changes tend to be followed by large changes, and small changes by small changes (Mandelbrot, 1963). Engle (1982) formalised this in the autoregressive conditional heteroscedasticity (ARCH) specification, for which he proposed the Lagrange-multiplier (LM) test that we employ in Section 4. Bollerslev (1986) generalised the framework to GARCH, which allows conditional variance to depend on its own lags as well as squared past innovations. Nelson (1991) introduced the EGARCH specification to capture asymmetric "leverage" effects, while Glosten, Jagannathan and Runkle (1993) proposed the GJR-GARCH alternative. Engle's (2002) Dynamic Conditional Correlation (DCC-GARCH) model extends the framework to multivariate settings. In emerging markets, Setiawan et al. (2021) document strong GARCH effects during the COVID-19 outbreak in Hungarian and Indonesian indices; Toma (2023) finds that GARCH-augmented ARIMA outperforms plain ARIMA in the Romanian IT sector. These contributions motivate our explicit testing for ARCH effects in all five return series and our acknowledgement that the conditional variance dimension is an important next step for future research.

2.6. Forecasting Challenges in Emerging and Frontier Markets

Frontier and emerging markets present forecasting challenges qualitatively distinct from developed venues. Speidell (2011) and Berger, Pukthuanthong and Yang (2011, 2013) document that frontier markets are typically characterised by limited investable opportunities, restricted foreign-investor access, low correlations with global benchmarks, and substantial idiosyncratic risk. Marshall, Nguyen and Visaltanachoti (2015) emphasise transaction-cost frictions, while Pukthuanthong and Roll (2009) propose alternative measures of market integration that capture multi-factor exposures more comprehensively than simple correlations. Birău (2015) provides comparative weak-form efficiency tests for Romania and Hungary in the post-2008 environment. The general consensus is that frontier markets exhibit predictability patterns inconsistent with strict EMH, but that the predictability is heterogeneous across assets and unstable over time – precisely the pattern we document for Uzbek bank stocks.

2.7. Market Microstructure Limitations in Low-Liquidity Markets

Where trading is thin, observed prices need not represent fully informed equilibrium values. Scholes and Williams (1977) first formalised the resulting non-synchronous trading bias in beta estimates; Dimson (1979) proposed the lag–lead correction now standard in thin-market applications. Lo and MacKinlay (1990) provide the formal econometric analysis of non-synchronous trading effects on autocorrelations and cross-correlations. Roll (1984) showed that bid–ask bounce induces a spurious negative serial correlation in transaction prices. These microstructure considerations are directly relevant to the Uzbek market: trading volumes for individual bank issuers are uneven, and certain assets (notably IPKY around the OTP acquisition closing) exhibited episodes of low daily turnover punctuated by abrupt re-pricings. We acknowledge these effects in our interpretation but do not formally implement Dimson corrections, leaving such robustness checks to future work.

2.8. Banking-Sector Stocks and Sensitivity to Market-Wide Indicators

Bank-stock prices are particularly sensitive to system-wide macro and financial-stability dynamics, given the pervasive role of banks in maturity transformation and credit intermediation. Beck, Demirgüç-Kunt and Levine (2006) document that banking-sector concentration interacts with crisis vulnerability across countries. Diebold and Yilmaz (2014) use VAR-based variance decompositions to construct connectedness measures for U.S. financial

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

firms. In the Uzbek context, four of the five largest commercial banks are state-owned or state-influenced; the IMF (2024, 2025) Article IV consultations emphasise the need to reduce state ownership of banking-system assets, strengthen risk-based supervision, and complete the first Financial Sector Assessment Program. These institutional features make the bank-stock segment of UZSE both empirically interesting and policy-relevant. The closest direct predecessor in the local literature is Eshov et al. (2021), who apply a structural-equation model to the Uzbek market during the COVID-19 pandemic. Akimov and Dollery (2009) and Alimov and Mukhamedov (2021) provide important institutional background on Uzbek capital-market reforms, but neither offers an econometric forecasting analysis of listed bank stocks. The present paper therefore extends the literature by furnishing the first integrated VAR-based forecasting study of UZSE bank issuers.

3. DATA AND METHODOLOGY

3.1. Data and Variable Construction

The empirical analysis uses daily closing-price data on four bank stocks listed on the Republican Stock Exchange "Toshkent" – Hamkorbank (HMKB), Sanoat Qurilish Bank (SQB), IPAK YO'LI Bank (IPKY) and Aloqabank (ALKB) – together with the Uzbekistan Composite Index (UCI), the principal market-wide benchmark of UZSE. The sample period runs from 9 September 2022 to 17 April 2026, yielding 883 daily price observations and 882 logarithmic returns. The sample selection reflects two practical considerations: (i) all four issuers were continuously traded with sufficient daily activity to support time-series modelling over the period; and (ii) the start date follows the post-pandemic stabilisation of the Uzbek financial system and immediately precedes the OTP-Ipoteka transaction closing of 13 June 2023, which represents the most economically significant ownership-structure event in the sample.

The four bank issuers span the cross-section of Uzbek banking-sector reform. HMKB is one of the leading private commercial banks (with International Finance Corporation and FMO as long-standing minority shareholders); SQB is the second-largest state-owned bank by assets, currently in the late stage of privatisation preparation supported by an Asian Development Bank, EBRD and IFC convertible-loan facility (Asian Development Bank, 2023); IPKY completed its first foreign privatisation through the OTP transaction; and ALKB is a state-owned bank scheduled for privatisation in the 2026–2027 window. The UCI index, launched on 29 August 2016 with a base value of 1,000 within the Korea Exchange-developed Unified Software and Technical Complex, captures aggregate listed-equity dynamics on UZSE.

Raw price data exhibited two technical inconsistencies that required correction: a subset of date entries was stored as text strings while others followed Excel serial format, and a small number of missing observations – attributable to public holidays and a limited number of non-trading days – needed to be reconciled. The cleaned panel is strictly chronological, contains no remaining missing values for the five series, and serves as the foundation for all downstream econometric work.

Table 1. Description of variables and data structure

Symbol	Issuer / index	Type	Obs.	Sample period
UCI	Uzbekistan Composite Index	Market index	883	09 Sep 2022 – 17 Apr 2026
HMKB	Hamkorbank	Listed stock	883	09 Sep 2022 – 17 Apr 2026
SQB	Sanoat Qurilish Bank (Uzpromstroybank)	Listed stock	883	09 Sep 2022 – 17 Apr 2026
IPKY	IPAK YO'LI Bank	Listed stock	883	09 Sep 2022 – 17 Apr 2026
ALKB	Aloqabank	Listed stock	883	09 Sep 2022 – 17 Apr 2026

Notes: All prices are end-of-day closing quotations expressed in Uzbek soum (UZS). Total trading days: 883. Logarithmic-return observations: 882.

3.2. Logarithmic Returns

Following standard practice in financial econometrics (Tsay, 2010; Campbell, Lo and MacKinlay, 1997), the analysis is conducted in continuously compounded (logarithmic) returns rather than raw price levels:

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \ln(P_t) - \ln(P_{t-1})$$

Three theoretical considerations justify the log-return transformation. First, log returns are time-additive: the multi-period return is the sum of single-period returns, a property essential for ARIMA forecasting. Second, log returns are typically closer to a Gaussian distribution than simple returns, reducing the impact of extreme positive movements on parametric estimates. Third, log returns avoid the asymmetry inherent in arithmetic returns, where a +50% gain followed by a -50% loss produces a -25% net return rather than zero. The return panel contains 882 observations per series.

3.3. Stationarity Testing

Given that financial price levels are typically integrated of order one, we test the stationarity of the return series rather than price levels. The Augmented Dickey–Fuller (ADF) test of Dickey and Fuller (1979) and Said and Dickey (1984) is implemented in three specifications (no drift / drift only / drift plus trend), with lag length selected by the Schwert (1989) rule. The null hypothesis is the presence of a unit root; rejection at conventional significance levels supports the use of stationary time-series models such as ARIMA and VAR on the return data. Stationarity is a necessary precondition for the validity of subsequent VAR analysis (Lütkepohl, 2005).

3.4. ARCH-LM Heteroscedasticity Testing

To assess volatility clustering, we apply Engle's (1982) Lagrange-multiplier test for autoregressive conditional heteroscedasticity. The test regresses squared OLS residuals on q lags of squared residuals; the test statistic $T \cdot R^2$ follows a $\chi^2(q)$ distribution under the null of no ARCH effects. Rejection of the null indicates conditional heteroscedasticity and motivates volatility-aware downstream modelling. While we do not estimate full GARCH models in the main analysis (preserving the focus on conditional-mean forecasting), we report annualised volatility statistics and a 30-day rolling volatility series to quantify time-varying risk.

3.5. Random Walk Benchmark

The Random Walk model serves as the forecasting benchmark. Under this specification, the optimal forecast at any future horizon h is the most recently observed price:

$$\hat{P}_{T+h} = P_T, h \in 1,2,\dots,H$$

The Random Walk benchmark provides the strictest test of any candidate forecasting model: a model that fails to outperform the random walk at the relevant horizon offers no economic value and should be rejected (Hyndman and Athanasopoulos, 2021). We employ this benchmark for all four bank stocks.

3.6. ARIMA Univariate Models

For each bank stock, an ARIMA(p, d, q) model is estimated on the natural logarithm of the price series, with p, d and q selected automatically via the Akaike Information Criterion. The ARIMA(p, d, q) specification combines an autoregressive polynomial of order p, an integration order d (the number of differences applied to achieve stationarity), and a moving-average polynomial of order q:

$$\phi(L)(1-L)^d \log(P_t) = c + \theta(L)\varepsilon_t, \varepsilon_t \sim WN(0,\sigma^2)$$

where L denotes the lag operator. ARIMA models are appropriate for univariate stock-price forecasting because they parsimoniously capture both short-run autocorrelation structure and any unit-root behaviour through the differencing parameter d. ARIMA forecasts are generated for a horizon of 63 trading days (approximately three calendar months).

3.7. VAR(4) Multivariate Specification

To exploit possible cross-asset dynamics, we estimate a vector autoregression on the joint return system ($y_t = (r_{UCI}, r_{HMKB}, r_{SQB}, r_{IPKY}, r_{ALKB})'$. The VAR(p) model is:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + u_t, u_t \sim WN(0,\Sigma),$$

with y_t the 5×1 vector of returns, c the intercept, A_i the K×K coefficient matrices, and Σ the residual covariance matrix. The optimal lag length p is selected from four standard information criteria – Akaike (AIC), Hannan–Quinn (HQ), Schwarz/Bayesian (SC) and Final Prediction Error (FPE). When the AIC and FPE criteria coincide, the joint signal is treated as decisive (Lütkepohl, 2005). The VAR system is judged stable if all roots of the characteristic polynomial lie inside the unit circle, equivalently if all eigenvalues of the companion matrix have modulus strictly less than one.

VAR is the natural multivariate framework for stock-return analysis because it imposes no a priori exogeneity restrictions and treats the joint dynamics symmetrically (Sims, 1980). It is particularly well suited to the present setting: we wish to test whether bank-stock returns predict one another, whether the aggregate UCI index Granger-causes individual bank returns, and whether the system as a whole exhibits meaningful cross-asset spillovers.

3.8. Residual Diagnostic Tests

VAR validity is assessed via three multivariate diagnostic tests. The Portmanteau (multivariate Ljung–Box) test of Hosking (1980, 1981) and Ljung and Box (1978) examines residual serial correlation; the

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

multivariate Jarque–Bera test of Doornik and Hansen (1994) decomposed into skewness and kurtosis components evaluates joint normality; and the multivariate ARCH-LM test (Lütkepohl, 2005, §16.5) tests for residual conditional heteroscedasticity. These diagnostics determine the credibility of standard inference and the robustness of impulse-response and forecast-error variance decomposition results.

3.9. Granger Causality

Granger (1969) defined causality in a predictive sense: variable X Granger-causes variable Y if the inclusion of past values of X in a forecasting equation for Y reduces the mean squared forecast error. Within the VAR framework, Granger non-causality from variable j to variable i corresponds to the joint hypothesis that the coefficients on lagged values of variable j in the equation for variable i are all equal to zero. The test statistic is asymptotically $\chi^2(p)$ under the null. We test, for each variable in turn, the joint Granger-causal effect on the remainder of the system.

3.10. Impulse Response and Forecast Error Variance Decomposition

Impulse Response Functions (IRFs) trace the dynamic effect of a one-standard-deviation orthogonal shock to one variable on the future values of all other variables in the system. We employ the Cholesky orthogonalisation, with bootstrap confidence intervals based on 100 replications. Forecast Error Variance Decomposition (FEVD) decomposes the h-step-ahead forecast error variance of each variable into the proportions attributable to each structural shock. FEVD provides a complementary perspective to Granger causality by quantifying the economic, rather than statistical, importance of cross-variable spillovers (Lütkepohl, 2005).

3.11. Out-of-Sample Forecast Accuracy

Forecast accuracy is evaluated using a chronological 80/20 train–test split. The first 80% of price observations (approximately 706 days) are used to estimate the candidate models, and the final 20% (approximately 177 days) constitute the out-of-sample evaluation period. For each bank, three competing forecasts are generated – Random Walk, ARIMA and VAR(4) – and three loss functions are computed:

$$RMSE = \sqrt{\text{mean}((y_t - \hat{y}_t)^2)};\ \ MAE = \text{mean}\ (\mid y_t - \hat{y}_t \mid);$$
$$MAPE = 100 \times \text{mean}\ \left(\frac{|y_t - \hat{y}_t|}{|y_t|}\right).$$

The best-performing model for each bank is selected primarily on lowest MAPE, with RMSE and MAE retained as supporting criteria. We acknowledge the well-known limitations of the MAPE statistic identified by Hyndman and Koehler (2006): MAPE is undefined when the actual value is zero, asymmetric (penalising over-forecasts more than under-forecasts), and scale-dependent in practice. We therefore interpret the cross-bank comparison qualitatively, focusing on the ordinal ranking of competing models within each bank rather than on cardinal MAPE differences across banks. The use of multiple complementary loss functions limits the practical influence of any single metric's pathologies.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics and Stylised Facts

Figure 1 plots the price dynamics of the UCI index and the four bank stocks over the sample period. Several features stand out. First, the UCI index trades within a relatively narrow range of approximately 600–700 points for most of the sample, before breaking out to a level above 900 in early 2026. Second, all four bank stocks display sharp idiosyncratic moves: HMKB more than quintuples from below 12 UZS in late 2022 to nearly 60 UZS by April 2026, IPKY exhibits an extreme spike in early 2024 followed by mean-reversion, SQB trades flat near 10 UZS for most of the sample before a sudden re-rating in early 2026, and ALKB shows a step-like pattern with a sharp drop in late 2024 and recovery in early 2026. The visible heterogeneity foreshadows the cross-bank differences in volatility and predictability that we document below.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

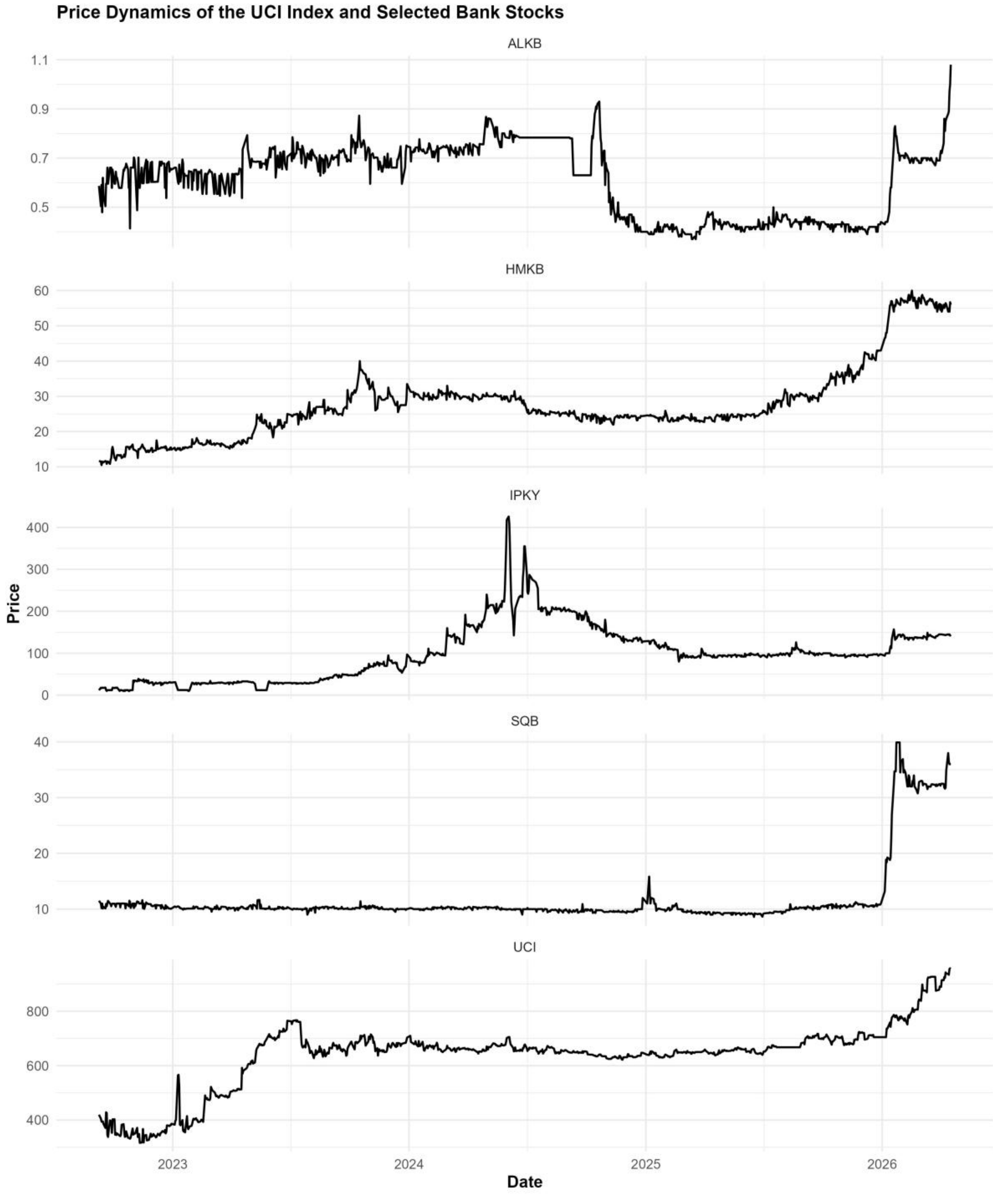

Figure 1. Price dynamics of the UCI index and the four selected bank stocks, 9 September 2022 – 17 April 2026 (daily closing values, UZS).

Figure 2 displays the corresponding logarithmic-return series. Returns fluctuate around zero with frequent large-amplitude moves, particularly in IPKY and ALKB. Periods of clustered volatility are visually apparent, motivating the formal ARCH-LM tests reported below.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

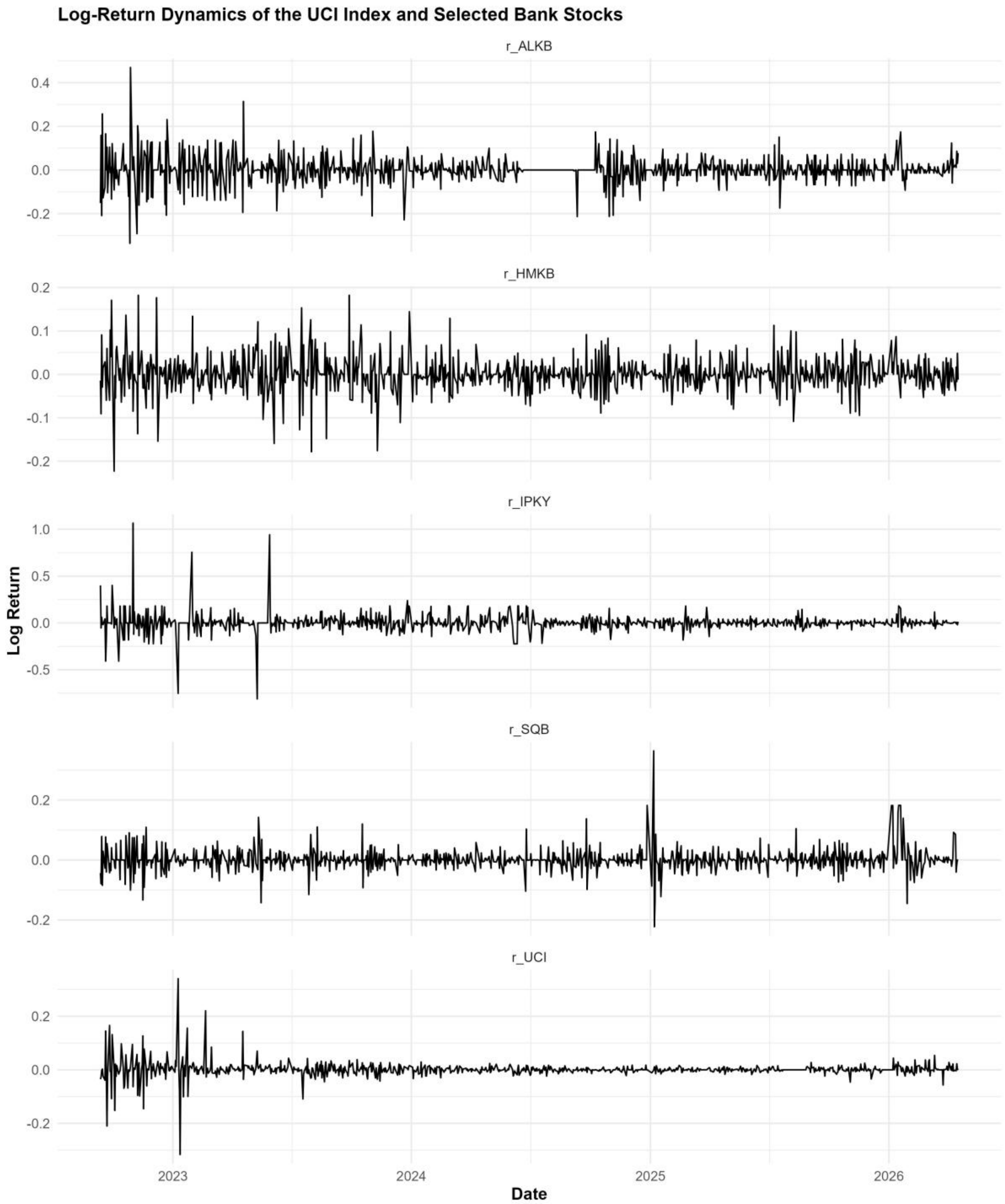

Figure 2. Daily log-return dynamics of the UCI index and the four selected bank stocks.

Table 2 reports descriptive statistics for the five log-return series. The annualised mean returns are economically sizeable: IPKY exhibits the highest daily mean (0.282%), followed by HMKB (0.178%), SQB (0.130%) and the UCI index (0.094%). Standard deviations reveal the substantial cross-sectional heterogeneity that motivates this study: IPKY is roughly 3.3 times more volatile than the UCI on a daily basis, while ALKB is 2.1 times more volatile and SQB and HMKB are approximately 1.3–1.4 times more volatile. All four bank stocks display extreme daily moves: IPKY records a single-day return as low as –81.2% and as high as +106.7%, indicative of episodic illiquidity-driven re-pricings. ALKB exhibits a maximum return of +47.0%, also pointing to episodic discontinuities.

Table 2. Descriptive statistics of log-returns

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

Variable	Mean	Std. dev.	Minimum	Maximum	Observations
r_{UCI}	0.000935	0.029263	−0.316651	0.340555	882
r_{HMKB}	0.001778	0.040741	−0.223037	0.182322	882
r_{SQB}	0.001295	0.038057	−0.222670	0.364012	882
r_{IPKY}	0.002823	0.096641	−0.811668	1.066828	882
r_{ALKB}	0.000692	0.061456	−0.336129	0.469804	882

Notes: Daily logarithmic returns. r_X denotes the return of variable X. Sample: 12 September 2022 – 17 April 2026.

Table 3 reports the contemporaneous correlation matrix. Off-diagonal correlations are uniformly small in absolute terms, with the largest absolute pairwise correlation – between r_{UCI} and r_{IPKY} – equal to only −0.1308. The bank-pair correlations themselves rarely exceed 0.06 in absolute value. Such weak contemporaneous co-movement is consistent with the characterisation of UZSE as a fragmented, low-liquidity venue where individual stock prices respond predominantly to issuer-specific information. It also offers an early empirical signal that simple market-model regressions of bank returns on the index would explain only a small share of variation, which is corroborated by the VAR equation-level R^2 statistics reported in Section 4.5.

Table 3. Correlation matrix of log-returns

Variable	r_{UCI}	r_{HMKB}	r_{SQB}	r_{IPKY}	r_{ALKB}
r_{UCI}	1.0000	0.0479	0.0281	−0.1308	0.0604
r_{HMKB}	0.0479	1.0000	0.0605	0.0141	0.0035
r_{SQB}	0.0281	0.0605	1.0000	0.0240	−0.0250
r_{IPKY}	−0.1308	0.0141	0.0240	1.0000	0.0234
r_{ALKB}	0.0604	0.0035	−0.0250	0.0234	1.0000

Notes: Pearson correlation coefficients of daily log returns over 882 observations.

4.2. Stationarity and Volatility Clustering

Table 4 reports the Augmented Dickey–Fuller stationarity tests and the Engle (1982) ARCH-LM heteroscedasticity tests for all five return series. The ADF statistics range from −7.03 (SQB) to −10.75 (IPKY), with corresponding p-values below 0.01 in every case. The null of a unit root is therefore rejected for all five series, confirming that the log-return data are stationary and that the use of level-stationary ARIMA and VAR specifications is methodologically appropriate.

ARCH-LM tests reject the null of conditional homoscedasticity at the 1% significance level for UCI ($\chi^2 = 205.23$, p = 2.71e-37), HMKB ($\chi^2 = 50.63$, p = 1.08e-06), SQB ($\chi^2 = 203.62$, p = 5.84e-37) and ALKB ($\chi^2 = 167.66$, p = 1.44e-29). For IPKY the ARCH-LM statistic is small and statistically insignificant ($\chi^2 = 0.69$, p = 1.000), indicating no evidence of conditional heteroscedasticity in this particular series – a finding consistent with the visual impression from Figure 2 that IPKY's volatility is dominated by occasional large discrete jumps rather than by clusters of moderately elevated variance. The detection of significant ARCH effects in four of the five series justifies our cautious interpretation of the conditional-mean forecasting results and motivates volatility-augmented extensions in future research.

Table 4. ADF stationarity and ARCH-LM heteroscedasticity tests

Variable	ADF stat.	ADF p	ARCH-LM χ^2	ARCH-LM p	Diagnosis
r_{UCI}	−10.5435	<0.01	205.23	2.71e-37	Stationary; ARCH
r_{HMKB}	−10.0483	<0.01	50.63	1.08e-06	Stationary; ARCH
r_{SQB}	−7.0321	<0.01	203.62	5.84e-37	Stationary; ARCH
r_{IPKY}	−10.7514	<0.01	0.69	1.0000	Stationary; no ARCH

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

Variable	ADF stat.	ADF p	ARCH-LM χ^2	ARCH-LM p	Diagnosis
r_{ALKB}	−9.5379	<0.01	167.66	1.44e-29	Stationary; ARCH

Notes: ADF test based on Said and Dickey (1984) with lag length selected by the Schwert (1989) rule. ARCH-LM test based on Engle (1982). All ADF p-values are reported at the 0.01 level, the smallest tabulated value in the standard MacKinnon (1996) critical-value table; the actual values are smaller.

4.3. Annualised and Rolling Volatility

Table 5 reports annualised volatility, computed as the standard deviation of daily log returns multiplied by sqrt(252). The cross-bank ranking is unambiguous: IPKY (153.41%) exceeds the volatility of any of the other three banks by a factor of at least 1.6; ALKB (97.56%) is the second-most volatile; HMKB (64.67%) and SQB (60.41%) are comparable and substantially less risky. The four-fold range across this small cross-section of bank issuers is a striking illustration of the heterogeneity that frontier-market practitioners must navigate.

Table 5. Annualised volatility of bank stocks

Bank stock	Annualised volatility (%)	Risk rank
IPKY	153.41	1 (most volatile)
ALKB	97.56	2
HMKB	64.67	3
SQB	60.41	4 (least volatile)

Notes: Annualised volatility = std(daily log returns) × sqrt(252).

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

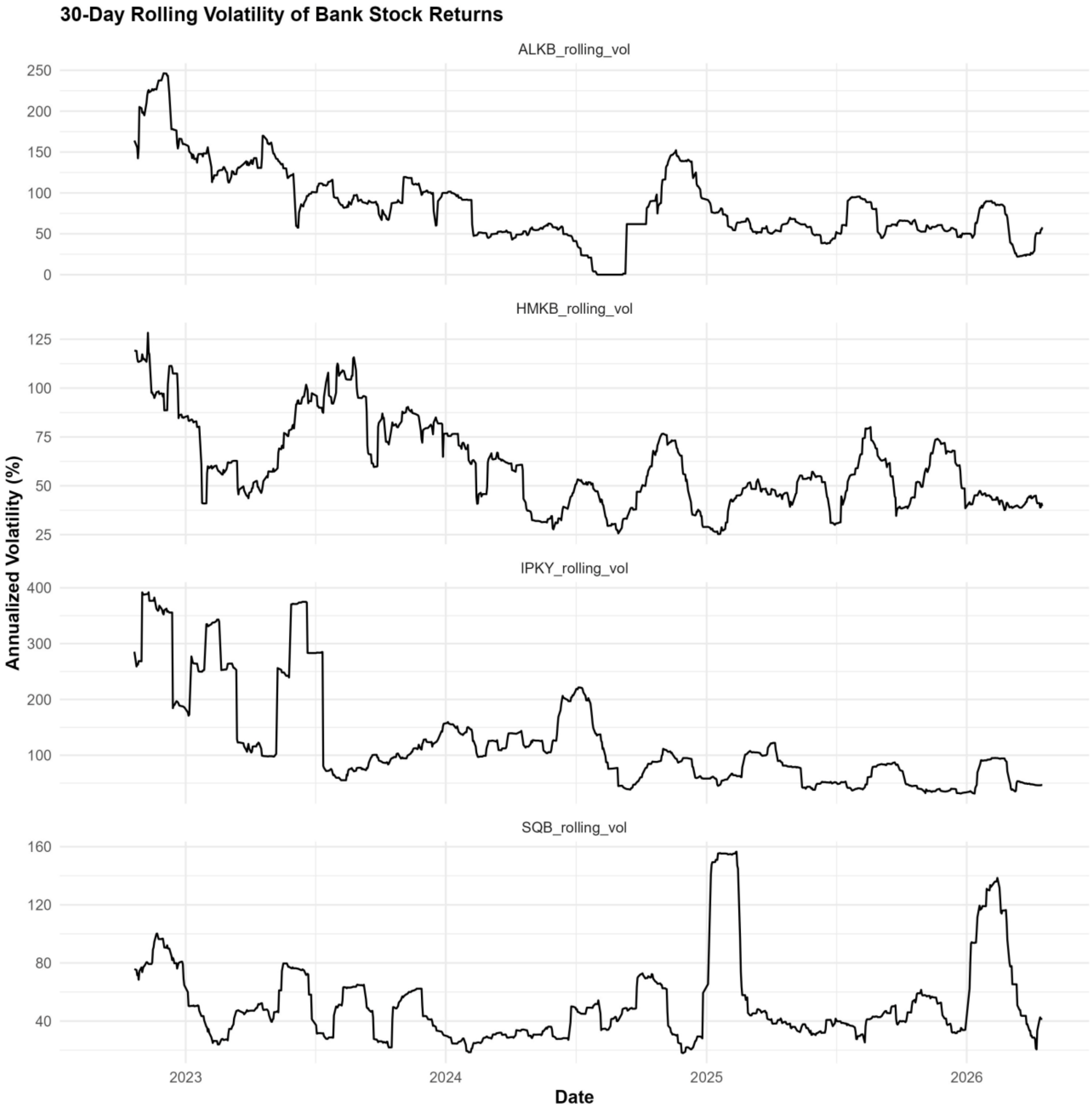

Figure 3. Thirty-day rolling annualised volatility of the four bank-stock returns, in percent.

Figure 3 reports 30-day rolling annualised volatility for each bank. The plots reveal three important patterns. First, volatility is markedly time-varying for all four banks. Second, IPKY exhibited very high volatility (above 300%) during 2022–2023, broadly contemporaneous with the OTP-Ipoteka transaction process, and stabilised at lower levels thereafter. Third, SQB displays a striking volatility regime shift in early 2025, when 30-day volatility briefly exceeded 150%, reflecting a one-off step change in the price level rather than chronic high-frequency turbulence. The episodic nature of high-volatility periods is itself an important stylised fact for forecasters: it implies that any model assuming constant variance will systematically misprice risk during regime shifts.

4.4. VAR Lag Selection and System Stability

Table 6 reports the four standard information criteria evaluated at lag lengths from 1 to 8. The criteria split: AIC and FPE both select lag 4, HQ selects lag 2, and SC selects lag 1. As discussed in Lütkepohl (2005), this pattern is unsurprising because SC imposes the heaviest parsimony penalty, AIC and FPE are less penalising and tend to favour richer dynamics, while HQ lies between them. We adopt VAR(4) as the main specification on the rationale that AIC and

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

FPE are jointly decisive when they coincide, and that the higher-lag specification provides a more conservative test of cross-bank dynamics. Robustness checks at lags 2 and 1 yield qualitatively similar substantive findings.

Table 6. VAR lag-order selection criteria

Criterion	Selected lag	Penalty intensity
AIC (Akaike)	4	Low
FPE (Final Prediction Error)	4	Low
HQ (Hannan–Quinn)	2	Moderate
SC (Schwarz / BIC)	1	High

Notes: Information criteria evaluated for VAR(p) on the joint return system $(r_{UCI}, r_{HMKB}, r_{SQB}, r_{IPKY}, r_{ALKB})'$ *with* $p \in \{1, 2, \dots, 8\}$..

The VAR(4) system is estimated on 878 effective observations (the full panel of 882 returns less the four lags). The maximum modulus of the characteristic-polynomial roots is 0.6377, comfortably below unity. The system is therefore stable, and impulse-response, FEVD and forecasting analyses can be performed within the conventional VAR framework. Equation-level coefficients of determination range from $R^2 = 0.0370$ for the IPKY equation to $R^2 = 0.2077$ for the ALKB equation; the HMKB and SQB equations sit at $R^2 = 0.1318$ and 0.1064 respectively, while the UCI equation has $R^2 = 0.0904$. The substantially higher fit of the ALKB equation indicates that ALKB returns are more closely tied to lagged values of the system as a whole than is the case for the other variables, while the much weaker IPKY fit indicates that IPKY return dynamics are dominated by issuer-specific shocks not captured in the linear lag structure.

4.5. VAR Residual Diagnostics

Table 7 reports the multivariate residual diagnostic tests. The Portmanteau (Hosking) statistic is 277.43 with 200 degrees of freedom (p = 0.0002385), rejecting the null of no residual serial correlation. The multivariate Jarque–Bera test rejects normality at p < 2.2e-16, with both the skewness component ($\chi^2 = 1{,}451.2$) and the kurtosis component ($\chi^2 = 129{,}556$) overwhelmingly significant. The multivariate ARCH-LM test rejects conditional homoscedasticity at p < 2.2e-16 ($\chi^2 = 5{,}750.4$).

These diagnostics imply that the VAR(4) residuals are not white noise. Three implications follow. First, classical asymptotic standard errors of the VAR coefficients understate true uncertainty and bootstrapped intervals should be used wherever inferential precision matters – hence our use of bootstrap confidence intervals in the IRF analysis. Second, the IRF point estimates remain valid as predictive dynamics under the standard interpretation but should not be read as fully structural causal effects. Third, the strong evidence of conditional heteroscedasticity confirms that a multivariate-GARCH extension (for example BEKK or DCC-GARCH) is the natural follow-up specification – a direction we leave for future research. We therefore interpret the VAR(4) results as evidence of short-term dynamic predictability rather than as a fully specified structural representation of the stock-return system.

Table 7. VAR(4) residual diagnostic tests

Test	χ^2	df	p-value	Conclusion
Portmanteau (Hosking) serial correlation	277.43	200	0.0002385	Reject H_0
Multivariate Jarque–Bera normality	131,007	10	<2.2e-16	Reject H_0
Skewness component	1,451.2	5	<2.2e-16	Reject
Kurtosis component	129,556	5	<2.2e-16	Reject
Multivariate ARCH-LM	5,750.4	2,700	<2.2e-16	Reject H_0

Notes: Multivariate residual diagnostic tests on VAR(4) residuals (T = 878 effective observations). H_0 *in each case is, respectively: no serial correlation, multivariate normality, no conditional heteroscedasticity.*

4.6. Granger Causality

Table 8 reports VAR(4) Granger-causality test statistics, where for each variable we test the joint hypothesis that its lagged values do not contribute to the prediction of the remaining four equations. Four of the five variables Granger-cause the system at conventional levels: ALKB does so most strongly (F = 2.94, p = 7.3e-05), followed by SQB

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

(F = 2.04, p = 0.0085), IPKY (F = 1.82, p = 0.0239) and HMKB (F = 1.75, p = 0.0323). By contrast, the UCI index does not Granger-cause the system (F = 1.00, p = 0.448). This is an empirically striking finding. In a typical liquid market one would expect the aggregate index to lead individual issuers because the index aggregates dispersed information more rapidly than thinly traded individual stocks. The opposite pattern in our data – idiosyncratic bank returns leading the system while the index does not – is consistent with two interpretations. First, the UCI index in its current form is heavily influenced by a small number of large-cap issuers whose news flow may not coincide with that of the bank-stock segment; second, the bank-stock segment itself contains material information that diffuses through the system before being reflected in index dynamics. Both interpretations are consistent with the broader literature on segmented frontier markets (Marshall, Nguyen and Visaltanachoti, 2015; Berger, Pukthuanthong and Yang, 2013).

Table 8. Granger causality test results

"Cause" variable	F-statistic	p-value	Significant at 5%
r_{UCI}	1.0049	0.4478	No
r_{HMKB}	1.7481	0.0323	Yes
r_{SQB}	2.0386	0.0085	Yes
r_{IPKY}	1.8157	0.0239	Yes
r_{ALKB}	2.9361	0.0000730	Yes

Notes: VAR(4) Granger non-causality tests. For each row, the null is that the lagged values of the listed variable do not enter the equations of the remaining four variables.

4.7. Impulse Response Functions

Figure 4 displays the impulse-response functions of each bank-stock return to a one-standard-deviation positive shock to the UCI index, with 95% bootstrap confidence intervals based on 100 replications. Three patterns are noteworthy. First, the responses are economically small in magnitude, generally bounded within ±0.02 across the 20-day horizon. Second, the responses are short-lived: in all four cases, point estimates return to a neighbourhood of zero within 5–7 trading days. Third, the patterns differ across banks. IPKY shows a clearly negative initial response – consistent with the negative contemporaneous correlation reported in Table 3 – followed by a partial rebound. HMKB exhibits a slightly positive initial response that quickly decays. SQB and ALKB show small positive initial responses with similarly rapid decay. The bootstrap intervals straddle zero at almost all horizons, indicating that the IRF point estimates are imprecisely estimated and statistical significance of the responses is weak. Substantively, this corroborates the Granger-causality finding that the UCI index is not a strong predictor of individual bank-stock returns.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

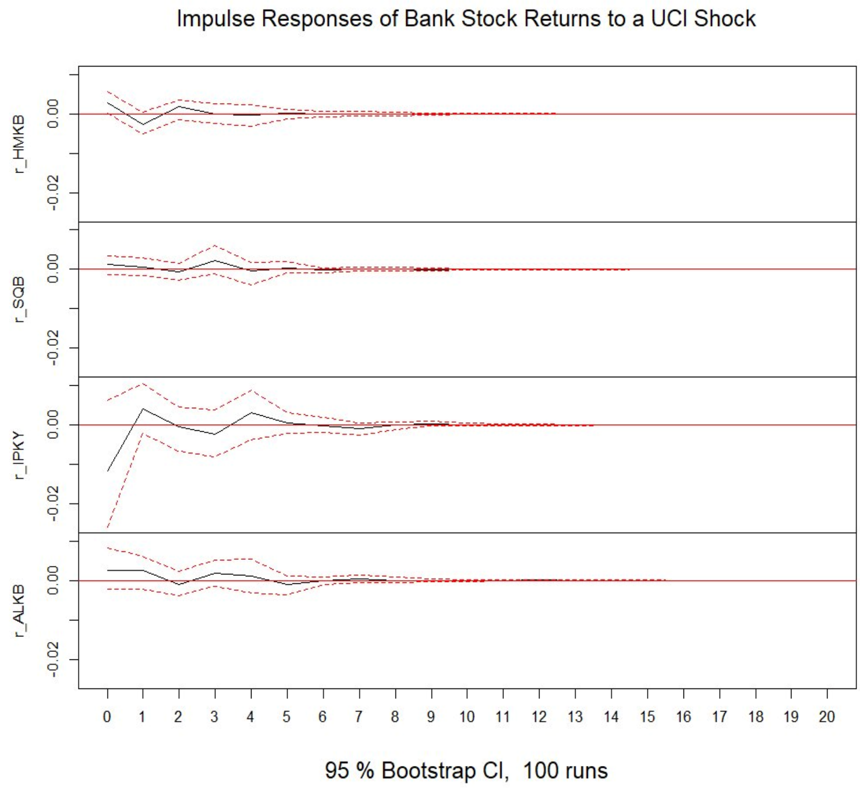

Figure 4. Impulse responses of bank-stock returns to a one-standard-deviation shock to the UCI index, with 95% bootstrap confidence intervals (100 replications).

4.8. Forecast Error Variance Decomposition

FEVD results at the 20-day horizon, presented in Table A1 of the Appendix, complement the Granger and IRF findings. Own-shock dominance is the central feature: each variable's own innovations explain between 94.79% (IPKY) and 98.00% (UCI) of its own 20-day forecast-error variance. The largest external contributor to any equation never exceeds 2%. UCI shocks explain only 1.82% of IPKY's forecast-error variance and 1.08% of HMKB's, while SQB shocks explain 1.96% of ALKB's forecast-error variance – the largest cross-bank spillover identified.

This pattern of strong own-shock dominance with weak cross-asset transmission is consistent with a segmented and thinly traded equity market in which information transmission across listed securities is incomplete (Diebold and Yilmaz, 2009; 2012). For a fully integrated equity market, one would expect the index shock alone to explain 10–20% or more of individual stock variance at a 20-day horizon; the figures we estimate are an order of magnitude smaller. This is a quantitatively important stylised fact about UZSE: short-term bank-stock variance is dominated by issuer-specific factors, with cross-bank and market-wide spillovers playing only a minor role.

4.9. Forecast Accuracy Comparison

The competing forecasting models are evaluated on the final 20% of the sample. Table 9 reports out-of-sample RMSE, MAE and MAPE for the Random Walk, ARIMA and VAR(4) forecasts of each bank stock's price level. The patterns are clear. For ALKB, the three models produce comparable accuracy, with VAR(4) marginally outperforming on MAPE (17.68% vs ARIMA 17.94% and Random Walk 18.99%). For HMKB, both ARIMA and VAR(4) substantially outperform the Random Walk benchmark, with VAR(4) selected on lowest MAPE (21.51%). For IPKY, VAR(4) produces a markedly lower MAPE (11.22%) than either Random Walk (13.63%) or ARIMA (16.05%), with corresponding gains in RMSE and MAE. For SQB, ARIMA achieves the lowest values on all three metrics (RMSE 14.65, MAE 9.69, MAPE 34.09%), narrowly outperforming the Random Walk and clearly outperforming VAR(4). The cross-bank pattern thus selects VAR(4) for ALKB, HMKB and IPKY and ARIMA for SQB – an outcome consistent with the underlying economic interpretation that ALKB, HMKB and IPKY benefit from the cross-asset information embedded in the multivariate framework, whereas SQB's near-flat return profile until early 2026 is best captured by its own internal time-series dynamics.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

Table 9. Out-of-sample forecast accuracy comparison

Bank	Model	RMSE	MAE	MAPE (%)	Best?
ALKB	Random Walk	0.1707	0.1220	18.9922	
ALKB	ARIMA	0.1764	0.1195	17.9428	
ALKB	VAR(4)	0.1884	0.1219	17.6788	✓
HMKB	Random Walk	18.0865	14.2333	28.2939	
HMKB	ARIMA	14.2955	11.0286	21.7082	
HMKB	VAR(4)	14.1877	10.9345	21.5128	✓
IPKY	Random Walk	26.9910	18.2695	13.6259	
IPKY	ARIMA	20.0150	16.9374	16.0460	
IPKY	VAR(4)	14.8164	11.4324	11.2249	✓
SQB	Random Walk	14.7599	9.8444	35.1839	
SQB	ARIMA	14.6535	9.6873	34.0880	✓
SQB	VAR(4)	14.8392	9.8850	35.2414	

Notes: 80/20 chronological train–test split. Lower values indicate better forecasting performance. The model with the lowest MAPE for each bank is marked with ✓.

Table 10 summarises the model selection.

Table 10. Best forecasting model by bank stock

Bank	Best model	RMSE	MAE	MAPE (%)
ALKB	VAR(4)	0.1884	0.1219	17.6788
HMKB	VAR(4)	14.1877	10.9345	21.5128
IPKY	VAR(4)	14.8164	11.4324	11.2249
SQB	ARIMA	14.6535	9.6873	34.0880

Notes: Best-performing model selected on lowest MAPE; RMSE and MAE are reported for cross-validation.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

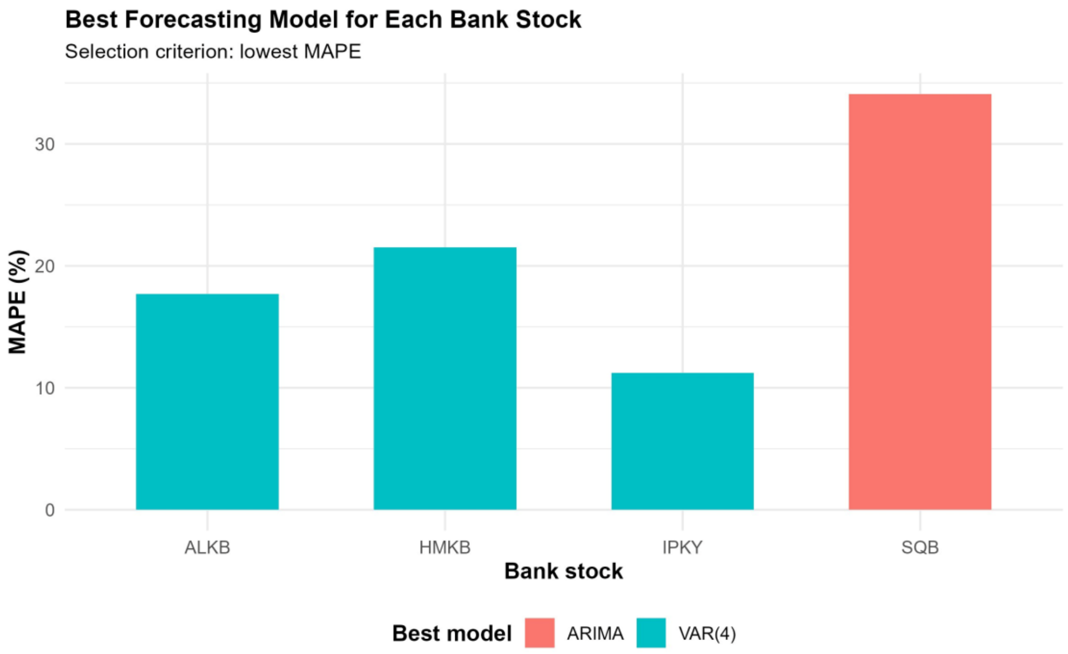

Figure 5. Best-performing forecasting model by bank stock based on lowest MAPE.

4.10. Final Three-Month Forecasts

Figure 6 presents the three-month price-path forecasts produced by the best-performing model for each bank. The solid lines display historical prices over the full sample and the dashed segments represent the model-implied forecasts over the 63-trading-day horizon (20 April 2026 to mid-July 2026).

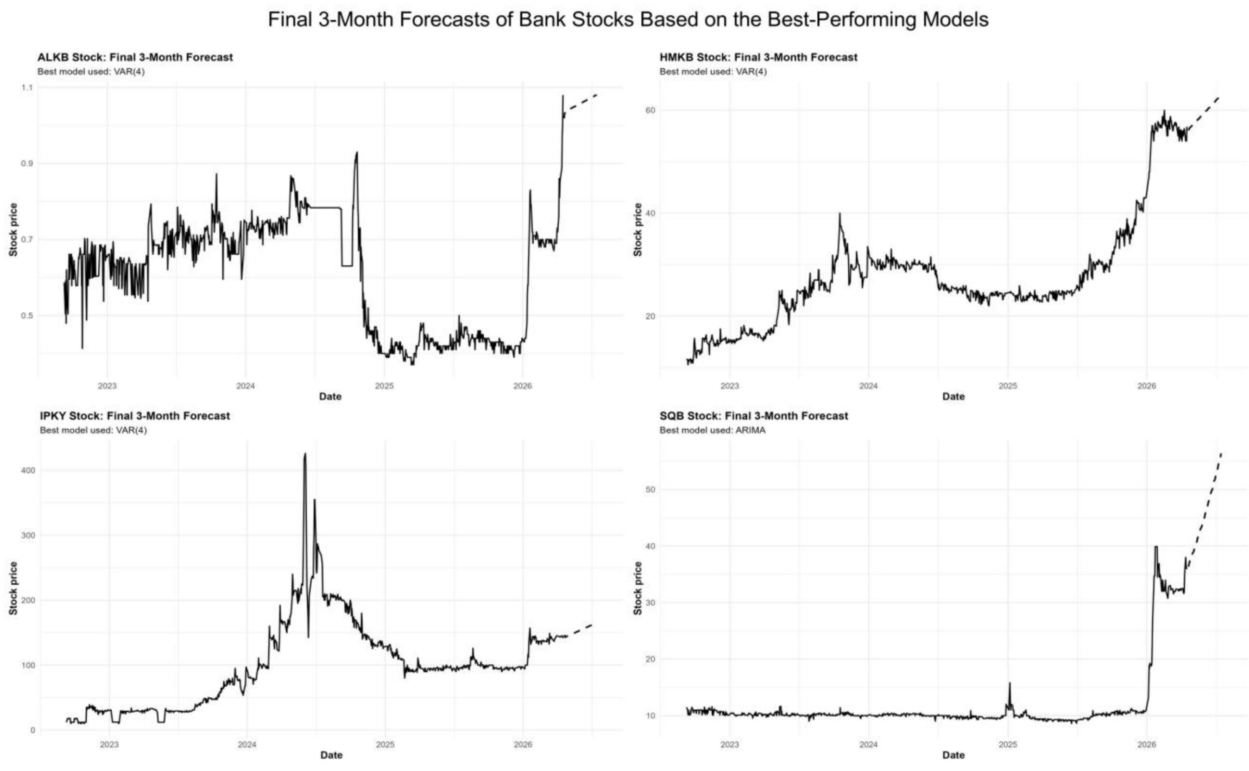

Figure 6. Three-month forecasts of bank-stock prices based on the best-performing model for each issuer.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

Table 11 quantifies the corresponding 1-, 2- and 3-month forecast price changes and assigns a directional signal. The pattern is heterogeneous. ALKB displays an essentially flat trajectory: the 3-month forecast price (1.0805 UZS) is virtually identical to the last observed price (1.0800 UZS), implying a 3-month change of just +0.04%. HMKB and IPKY both display moderate positive trajectories, with 3-month price increases of approximately +12.49% and +15.04% respectively. SQB exhibits the largest projected increase, at +56.63%, although this magnitude warrants caution given the model's sensitivity to the rapid SQB price re-rating in early 2026.

Table 11. Final three-month forecast results and directional signals

Bank	Model	Last price (UZS)	3-month forecast (UZS)	3-month Δ (%)	Signal
ALKB	VAR(4)	1.0800	1.0805	+0.04	Sideways / stable
HMKB	VAR(4)	56.0000	62.9919	+12.49	Moderate growth
IPKY	VAR(4)	143.9900	165.6450	+15.04	Stronger growth
SQB	ARIMA	36.0000	56.3884	+56.63	Strong growth (caution)

Notes: Forecast horizon = 63 trading days (≈20 April 2026 – 15 July 2026). Forecasts are model-based projections, not deterministic predictions. SQB's magnitude reflects an extrapolation of recent trend and should be interpreted with particular caution.

5. DISCUSSION

5.1. Implications for Market Efficiency in Uzbekistan

The empirical pattern documented in Section 4 carries direct implications for the informational efficiency of the Uzbek bank-stock segment. Three findings are particularly informative. First, the substantial out-of-sample superiority of VAR(4) over the Random Walk benchmark for three of four banks is a direct rejection of the strict random-walk corollary of weak-form market efficiency – multivariate lag dynamics contain economically meaningful predictive information at a 3-month horizon. Second, however, the forecasting gains are concentrated in specific stocks (notably IPKY and HMKB) and absent for ALKB, where the three models perform comparably. Third, the dominance of own-shock contributions in the FEVD (94.79–98.00% at the 20-day horizon) implies that even where predictability exists, it operates predominantly through stock-specific channels rather than through aggregate information transmission. These findings are consistent with what Berger, Pukthuanthong and Yang (2013) describe as the typical pattern in frontier markets: heterogeneous and intermittent predictability arising from limited liquidity, fragmented price discovery and segmented information sets, rather than from systematic mispricing of macro factors.

5.2. Short-Term Predictability of Bank Stocks

The cross-bank heterogeneity of forecasting performance is itself an empirical regularity. Where multivariate frameworks outperform – as for ALKB, HMKB and IPKY – the gain reflects the value of cross-asset information that is not captured in stock-by-stock specifications. Where univariate ARIMA outperforms – as for SQB – the gain reflects the dominance of the stock's own internal time-series structure relative to the cross-asset signal. Practitioners working in the Uzbek market should therefore expect that no single forecasting framework dominates across the bank-stock segment, and should adopt issuer-specific model-selection procedures. This conclusion echoes the broader emerging-market forecasting literature (Reddy, 2019; Bhowmik et al., 2022; Shogole et al., 2024).

The interpretation of SQB's 56.63% 3-month projected increase deserves particular emphasis. The forecast reflects the linear extrapolation of a strong trend visible in the late-sample data, and the underlying ARIMA(0, 2, 2) specification captures persistent drift. In a deeper, more liquid market with transparent disclosure, such an extrapolation might be plausible. In the Uzbek context, however, three caveats are necessary. First, SQB is preparing for privatisation, and price formation may be influenced by privatisation-process news flow that is not modelled here. Second, episodic illiquidity can produce sharp re-pricings that linear models extrapolate too aggressively. Third, MAPE of 34.09% – the highest among the four bank stocks – indicates that the SQB forecast carries the largest expected error in proportional terms. We therefore present the SQB forecast as a model-implied projection rather than a directional investment recommendation.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

5.3. The Role of UCI as a Market-Wide Indicator

The empirical evidence on the role of the UCI index is sobering. The Granger-causality test fails to reject the null that UCI does not predict the bank-stock system (p = 0.448), and the FEVD shows that UCI shocks explain only 0.5–1.8% of bank-stock variance at the 20-day horizon. Two interpretations are possible. The first is methodological: the UCI weighting scheme or its constituent universe may underweight banking-sector representation, so that the index signals are dominated by non-bank issuers. The second is structural: even a well-constructed index will exhibit weak short-run leadership in a thin market where individual securities trade infrequently and at idiosyncratic news flow. Both interpretations lead to similar policy conclusions: improving the methodological transparency of the UCI, broadening its constituent base, and increasing the depth of trading activity would all enhance its informational role.

5.4. Segmentation and Weak Information Transmission

The very high own-shock dominance documented in the FEVD is the single most consequential empirical finding of the paper. It implies that the four bank stocks behave more like four loosely related independent assets than like four members of a tightly integrated banking-sector cluster. The largest cross-bank spillover identified – SQB shocks explaining 1.96% of ALKB's 20-day variance – is economically negligible compared to typical spillover magnitudes documented for U.S. or European bank stocks (Diebold and Yilmaz, 2014). This pattern is consistent with the structural features of the Uzbek market: only a subset of the 36 commercial banks operating in Uzbekistan is listed; trading volume is concentrated in a small number of large transactions; institutional investor participation is limited; and disclosure quality, while improving, remains uneven. As market reforms proceed – especially the privatisations of SQB and ALKB and the progress of UzNIF as a domestic institutional investor – we would expect cross-bank spillovers to gradually strengthen. Re-estimating this analysis on a longer post-reform sample will be a useful test of that prediction.

5.5. Implications for Investor Decision-Making

For market participants, three practical implications follow. First, the heterogeneity of bank-stock volatility (60% to 153% on an annualised basis) implies that risk-adjusted portfolio construction requires explicit cross-stock weighting; an equally weighted portfolio would be dominated by IPKY's volatility. Second, the limited cross-asset spillovers imply that diversification across the four bank stocks materially reduces idiosyncratic risk, but offers little protection against system-wide shocks. Third, the finding that VAR(4) outperforms ARIMA and Random Walk for three of four issuers suggests that practitioners using univariate models alone may be leaving forecast value on the table. None of these conclusions, however, should be interpreted as investment recommendations: model-based forecasts are probabilistic, not deterministic, and their accuracy can deteriorate sharply in regime-shift environments.

5.6. Implications for Regulators and the Stock Exchange

For regulators and the stock exchange, the findings highlight the need to improve market liquidity, disclosure quality, trading transparency and index representativeness. Stronger market infrastructure may enhance information transmission, reduce excessive volatility and improve the reliability of price discovery in Uzbekistan's equity market. Specific regulatory priorities suggested by the empirical results include: (i) deepening the listed-issuer pool to broaden the UCI's informational base, including through the privatisations of SQB and ALKB; (ii) strengthening daily disclosure requirements to reduce the information asymmetries that produce episodic large-amplitude returns; (iii) improving market-making arrangements to address the thin-trading episodes that distort short-run price formation; and (iv) developing supplementary indices for sub-segments of the market – notably a banking-sector index – that would aid both research and investor understanding.

6. CONCLUSION

This paper has provided a comprehensive short-term forecasting analysis of bank stocks listed on the Republican Stock Exchange "Toshkent" using daily data over 9 September 2022 to 17 April 2026. By integrating benchmark, univariate and multivariate forecasting frameworks within a unified empirical design, the study yields five main contributions to the literature on emerging frontier markets.

First, all log-return series are stationary, and four of five exhibit highly significant ARCH effects, confirming the volatility clustering that is a stylised fact of financial returns globally and motivating a cautious interpretation of conditional-mean forecasting results. Second, the VAR(4) system is statistically stable, with maximum characteristic root 0.6377, and equation-level explanatory power varies markedly across banks, ranging from $R^2 = 0.0370$ for IPKY to $R^2 = 0.2077$ for

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

ALKB. Third, residual diagnostic tests reveal serial correlation, non-normality and conditional heteroscedasticity – limitations that are explicitly acknowledged and that motivate volatility-augmented extensions in future research. Fourth, forecast error variance decomposition reveals strong own-shock dominance ranging from 94.79% to 98.00% at the 20-day horizon, indicating that the Uzbek bank-stock market remains substantially segmented in the short run. Fifth, out-of-sample comparisons select VAR(4) as the best-performing model for ALKB, HMKB and IPKY and ARIMA for SQB, with three-month projected price changes of +0.04%, +12.49%, +15.04% and +56.63% respectively.

These findings substantiate the usefulness of combining benchmark, univariate and multivariate models in bank-stock forecasting. The Uzbek stock market exhibits features typical of emerging frontier markets: limited cross-asset transmission, persistent volatility clustering, short-run predictability gains relative to a random walk, and heterogeneous forecasting performance across securities. By documenting these patterns systematically and by relating them explicitly to the ongoing capital-market reform agenda – including bank privatisation, the establishment of the National Investment Fund, and the modernisation of the UZSE trading infrastructure – the paper contributes both to the comparative econometric literature on frontier markets and to the policy debate on Uzbek financial development. The reform priorities highlighted by the analysis include broadening the listed-issuer base, deepening market liquidity, strengthening disclosure quality, and improving the representativeness of the aggregate index.

7. LIMITATIONS AND FUTURE RESEARCH

Several limitations bound the interpretation of our findings and motivate clear extensions. First, residual diagnostic tests reject white-noise behaviour of the VAR(4) residuals. We have therefore interpreted the VAR results as short-term dynamic predictability rather than as a fully structural specification. The natural extension is to estimate multivariate GARCH models – BEKK, DCC-GARCH (Engle, 2002), or copula-GARCH – to capture conditional volatility and time-varying correlations alongside the conditional mean.

Second, the analysis does not include trading-volume or liquidity variables, both of which are theoretically relevant in thinly traded markets where price formation is endogenous to trading activity. Future work should incorporate volume-based information, ideally through volume-augmented VAR or PVAR specifications and through bid–ask-spread proxies where available.

Third, we do not formally implement the Scholes–Williams (1977) or Dimson (1979) lag–lead corrections for non-synchronous trading. While the impact of such corrections is likely modest for the four most actively traded UZSE bank stocks during 2022–2026, a formal robustness check would strengthen the paper's referee defence and is high on the priority list for future revisions.

Fourth, the SQB three-month forecast of +56.63% should be interpreted cautiously. Short-term stock forecasts in low-liquidity emerging markets are sensitive to market microstructure effects, trading-volume fluctuations and abrupt price adjustments that are not captured by linear models. The Diebold and Mariano (1995) test could be applied to formally test the statistical significance of the VAR-versus-ARIMA accuracy differences, providing additional confidence in the model-selection conclusions.

Fifth, time-varying parameter VAR (TVP-VAR) and structural-break (Bai–Perron) extensions could explicitly accommodate the OTP-Ipoteka regime change of June 2023, the SQB price re-rating of early 2026, and the prospective ALKB privatisation. Sixth, broader cross-country comparisons – with neighbouring CIS markets such as Kazakhstan's KASE, or with frontier comparators such as Vietnam, Bangladesh or Romania – would situate the Uzbek findings within a wider emerging-market context. These extensions are left to future research – l

REFERENCES

1. Adebiyi, A. A., Adewumi, A. O. and Ayo, C. K. (2014) 'Comparison of ARIMA and artificial neural networks models for stock price prediction', Journal of Applied Mathematics, 2014, Article 614342. doi: 10.1155/2014/614342.
2. Akimov, A. and Dollery, B. (2009) 'Financial development policies in Uzbekistan: an analysis of achievements and failures', Economic Change and Restructuring, 42(4), pp. 293–318. doi: 10.1007/s10644-009-9075-7.
3. Alimov, O. and Mukhamedov, F. (2021) 'The stock market in Uzbekistan as the backbone of country's economic development', SSRN Working Paper No. 3917735.
4. Asian Development Bank (2023) ADB, SQB sign $50 million loan to support privatization and expand lending to MSMEs in Uzbekistan.

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

Manila: Asian Development Bank, 10 November.
5. Bachelier, L. (1900) 'Théorie de la spéculation', Annales scientifiques de l'École Normale Supérieure, 3rd ser., 17, pp. 21–86.
6. Beck, T., Demirgüç-Kunt, A. and Levine, R. (2006) 'Bank concentration, competition, and crises: first results', Journal of Banking & Finance, 30(5), pp. 1581–1603.
7. Berger, D., Pukthuanthong, K. and Yang, J. J. (2011) 'International diversification with frontier markets', Journal of Financial Economics, 101(1), pp. 227–242. doi: 10.1016/j.jfineco.2011.02.009.
8. Berger, D., Pukthuanthong, K. and Yang, J. J. (2013) 'Is the diversification benefit of frontier markets realizable by mean-variance investors? The evidence of investable funds', Journal of Portfolio Management, 39(4), pp. 36–48.
9. Bhowmik, R., Debnath, G. C., Debnath, N. C. and Wang, S. (2022) 'Emerging stock market reactions to shocks during various crisis periods', PLoS ONE, 17(9), e0272450. doi: 10.1371/journal.pone.0272450.
10. Birău, F. (2015) 'Emerging capital market efficiency: a comparative analysis of weak-form efficiency in Romania and Hungary in the context of the global financial crisis', AI & Society, 30(2), pp. 223–233.
11. Bollerslev, T. (1986) 'Generalized autoregressive conditional heteroskedasticity', Journal of Econometrics, 31(3), pp. 307–327. doi: 10.1016/0304-4076(86)90063-1.
12. Box, G. E. P. and Jenkins, G. M. (1970) Time series analysis: forecasting and control. San Francisco: Holden-Day.
13. Box, G. E. P., Jenkins, G. M., Reinsel, G. C. and Ljung, G. M. (2015) Time series analysis: forecasting and control. 5th edn. Hoboken, NJ: Wiley.
14. Brooks, C. (2019) Introductory econometrics for finance. 4th edn. Cambridge: Cambridge University Press.
15. Campbell, J. Y., Lo, A. W. and MacKinlay, A. C. (1997) The econometrics of financial markets. Princeton, NJ: Princeton University Press.
16. CEIC Data (2026) Uzbekistan market capitalization and Uzbekistan equity market index, August 2016 – April 2026. CEIC Data Manager.
17. Chow, K. V. and Denning, K. C. (1993) 'A simple multiple variance ratio test', Journal of Econometrics, 58(3), pp. 385–401.
18. Chowdhury, T. U. and Islam, M. S. (2021) 'ARIMA time series analysis in forecasting daily stock price of Chittagong Stock Exchange', International Journal of Research and Innovation in Social Science, 5(6), pp. 214–233.
19. Dickey, D. A. and Fuller, W. A. (1979) 'Distribution of the estimators for autoregressive time series with a unit root', Journal of the American Statistical Association, 74(366a), pp. 427–431. doi: 10.1080/01621459.1979.10482531.
20. Diebold, F. X. and Mariano, R. S. (1995) 'Comparing predictive accuracy', Journal of Business & Economic Statistics, 13(3), pp. 253–263.
21. Diebold, F. X. and Yilmaz, K. (2009) 'Measuring financial asset return and volatility spillovers, with application to global equity markets', Economic Journal, 119(534), pp. 158–171.
22. Diebold, F. X. and Yilmaz, K. (2012) 'Better to give than to receive: predictive directional measurement of volatility spillovers', International Journal of Forecasting, 28(1), pp. 57–66.
23. Diebold, F. X. and Yilmaz, K. (2014) 'On the network topology of variance decompositions: measuring the connectedness of financial firms', Journal of Econometrics, 182(1), pp. 119–134.
24. Dikshit, A. and Singh, H. (2019) 'Estimating and forecasting volatility using ARIMA model: a study on NSE, India', Indian Journal of Finance, 13(5), pp. 35–51.
25. Dimson, E. (1979) 'Risk measurement when shares are subject to infrequent trading', Journal of Financial Economics, 7(2), pp. 197–226.
26. Doornik, J. A. and Hansen, H. (1994) An omnibus test for univariate and multivariate normality. Working Paper, University of Oxford.
27. Engle, R. F. (1982) 'Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation', Econometrica, 50(4), pp. 987–1007.
28. Engle, R. F. (2002) 'Dynamic conditional correlation: a simple class of multivariate generalized autoregressive conditional

World Economics & Finance Bulletin (WEFB)
Available Online at: https://www.scholarexpress.net
Vol. 58, May, 2026
ISSN: 2749-3628,

heteroskedasticity models', Journal of Business & Economic Statistics, 20(3), pp. 339–350.

29. Eshov, M., Osamy, W., Aziz, A. and Khedr, A. M. (2021) 'Econometric analysis of stock market performance during COVID-19 pandemic: a case study of Uzbekistan stock market', International Journal of Advanced Computer Science and Applications, 12(4), pp. 217–224.
30. Fama, E. F. (1970) 'Efficient capital markets: a review of theory and empirical work', Journal of Finance, 25(2), pp. 383–417.
31. Fama, E. F. (1991) 'Efficient capital markets: II', Journal of Finance, 46(5), pp. 1575–1617.
32. Glosten, L. R., Jagannathan, R. and Runkle, D. E. (1993) 'On the relation between the expected value and the volatility of the nominal excess return on stocks', Journal of Finance, 48(5), pp. 1779–1801.
33. Granger, C. W. J. (1969) 'Investigating causal relations by econometric models and cross-spectral methods', Econometrica, 37(3), pp. 424–438.
34. Grossman, S. J. and Stiglitz, J. E. (1980) 'On the impossibility of informationally efficient markets', American Economic Review, 70(3), pp. 393–408.
35. Hamilton, J. D. (1994) Time series analysis. Princeton, NJ: Princeton University Press.
36. Hoque, H. A. A. B., Kim, J. H. and Pyun, C. S. (2007) 'A comparison of variance ratio tests of random walk: a case of Asian emerging stock markets', International Review of Economics & Finance, 16(4), pp. 488–502.
37. Hosking, J. R. M. (1980) 'The multivariate portmanteau statistic', Journal of the American Statistical Association, 75(371), pp. 602–608.
38. Hyndman, R. J. and Athanasopoulos, G. (2021) Forecasting: principles and practice. 3rd edn. Melbourne: OTexts.
39. Hyndman, R. J. and Koehler, A. B. (2006) 'Another look at measures of forecast accuracy', International Journal of Forecasting, 22(4), pp. 679–688. doi: 10.1016/j.ijforecast.2006.03.001.
40. International Monetary Fund (2024) Republic of Uzbekistan: 2024 Article IV Consultation – Press release; and Staff report. IMF Country Report No. 2024/210. Washington, DC: International Monetary Fund.
41. International Monetary Fund (2025) Uzbekistan: Staff concluding statement of the 2025 Article IV mission, 23 April. Washington, DC: International Monetary Fund.
42. Ljung, G. M. and Box, G. E. P. (1978) 'On a measure of lack of fit in time series models', Biometrika, 65(2), pp. 297–303.
43. Lo, A. W. and MacKinlay, A. C. (1988) 'Stock market prices do not follow random walks: evidence from a simple specification test', Review of Financial Studies, 1(1), pp. 41–66.
44. Lo, A. W. and MacKinlay, A. C. (1990) 'An econometric analysis of nonsynchronous trading', Journal of Econometrics, 45(1–2), pp. 181–211.
45. Lo, A. W. and MacKinlay, A. C. (1999) A non-random walk down Wall Street. Princeton, NJ: Princeton University Press.
46. Lütkepohl, H. (2005) New introduction to multiple time series analysis. Berlin: Springer.
47. MacKinnon, J. G. (1996) 'Numerical distribution functions for unit root and cointegration tests', Journal of Applied Econometrics, 11(6), pp. 601–618.
48. Marshall, B. R., Nguyen, N. H. and Visaltanachoti, N. (2015) 'Frontier market transaction costs and diversification', Journal of Financial Markets, 24, pp. 1–24.
49. Nelson, D. B. (1991) 'Conditional heteroskedasticity in asset returns: a new approach', Econometrica, 59(2), pp. 347–370.
50. Nguyen, T. T. H., Naeem, M. A., Balli, F., Balli, H. O. and Vo, X. V. (2022) 'Sectoral volatility spillovers and their determinants in Vietnam', Economic Change and Restructuring, 55, pp. 2235–2269.
51. OTP Group (2023) OTP Bank acquires Uzbekistan's Ipoteka Bank, 13 June. Budapest: OTP Group.
52. Pesaran, M. H. and Shin, Y. (1998) 'Generalised impulse response analysis in linear multivariate models', Economics Letters, 58(1), pp. 17–29.
53. Pukthuanthong, K. and Roll, R. (2009) 'Global market integration: an alternative measure and its application', Journal of Financial Economics, 94(2), pp. 214–232.
54. Reddy, C. V. (2019) 'Predicting the stock market index using stochastic time series ARIMA modeling: the sample of BSE and NSE', Indian Journal of Finance, 13(8), pp. 7–25.
55. Roll, R. (1984) 'A simple implicit measure of the effective bid-ask spread in an efficient market', Journal of Finance, 39(4), pp. 1127–1139.

56. Said, S. E. and Dickey, D. A. (1984) 'Testing for unit roots in autoregressive-moving average models of unknown order', Biometrika, 71(3), pp. 599–607.
57. Samuelson, P. A. (1965) 'Proof that properly anticipated prices fluctuate randomly', Industrial Management Review, 6(2), pp. 41–49.
58. Scholes, M. and Williams, J. (1977) 'Estimating betas from nonsynchronous data', Journal of Financial Economics, 5(3), pp. 309–327.
59. Schwert, G. W. (1989) 'Tests for unit roots: a Monte Carlo investigation', Journal of Business & Economic Statistics, 7(2), pp. 147–159.
60. Setiawan, B., Ben Abdallah, M., Fekete-Farkas, M., Nathan, R. J. and Zeman, Z. (2021) 'GARCH (1,1) models and analysis of stock market turmoil during COVID-19 outbreak in an emerging and developed economy', Journal of Risk and Financial Management, 14(12), 576.
61. Shogole, L. M. P., Nwanamidwa, S., Chanza, M., Munapo, E. and Mpeta, K. N. (2024) 'Modeling and forecasting bank stock prices: GARCH and ARIMA approaches', in Vasant, P. et al. (eds) Intelligent computing and optimization. Lecture Notes in Networks and Systems, vol. 854. Cham: Springer, pp. 130–141.
62. Sims, C. A. (1980) 'Macroeconomics and reality', Econometrica, 48(1), pp. 1–48.
63. Speidell, L. S. (2011) Frontier market equity investing: finding the winners of the future. Charlottesville, VA: CFA Institute Research Foundation.
64. Spot.uz (2026) UZNIF announced the start of an IPO – investors will be offered about 30% of shares, 30 April. Tashkent: Spot.
65. Stock, J. H. and Watson, M. W. (2001) 'Vector autoregressions', Journal of Economic Perspectives, 15(4), pp. 101–115.
66. Toma, L. R. (2023) 'Exploring the effectiveness of ARIMA and GARCH models in stock price forecasting: an application in the IT industry', Informatica Economica, 27(3), pp. 61–72.
67. Tsay, R. S. (2010) Analysis of financial time series. 3rd edn. Hoboken, NJ: Wiley.
68. U.S. Department of State (2025) 2025 investment climate statements: Uzbekistan. Washington, DC: U.S. Department of State.

Appendix

Table A1. Forecast Error Variance Decomposition at the 20-day horizon (%)

Variable	Own	UCI	HMKB	SQB	IPKY	ALKB
r_UCI	98.00	–	0.57	0.25	0.75	0.43
r_HMKB	96.82	1.08	–	0.51	0.40	1.18
r_SQB	96.04	0.52	0.64	–	1.14	1.66
r_IPKY	94.79	1.82	0.83	0.75	–	1.80
r_ALKB	95.59	0.54	1.38	1.96	0.53	–

Notes: Each row reports the percentage contribution of innovations in the column variables to the 20-day forecast-error variance of the row variable. "Own" denotes own-shock contribution. Rows sum to approximately 100% (rounding).

Table A2. ARIMA model specifications and information criteria

Bank	ARIMA model	AIC	BIC
HMKB	ARIMA(1, 1, 1) with drift	−3,237.43	−3,218.30
SQB	ARIMA(0, 2, 2)	−3,305.75	−3,291.41
IPKY	ARIMA(4, 1, 1) with drift	−1,620.21	−1,586.73
ALKB	ARIMA(0, 1, 1)	−2,589.63	−2,580.06

Notes: ARIMA orders selected automatically using the Akaike Information Criterion. AIC and BIC are computed on the log-price series.