

Forecasting Weekly Returns of the Tehran Stock Exchange Total Index Using the MIDAS Model

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Abstract: Forecasting capital market returns plays a pivotal role in the decision-making processes of investors, portfolio managers, and economic policymakers. Because economic variables are observed at different temporal frequencies, conventional temporal aggregation of data may result in the loss of valuable within-period information. The primary objective of this study is to evaluate the out-of-sample forecasting performance for weekly returns of the Tehran Stock Exchange (TSE) Total Index using a Mixed Data Sampling (MIDAS) regression model with a Beta polynomial weighting function. For this purpose, daily data on changes in the exchange rate, changes in the global gold price, changes in oil prices, daily index returns, and daily conditional volatilities extracted from a GARCH(1,1) model over the 2016–2025 period were employed. Model performance was evaluated using an out-of-sample forecasting-window approach by comparing forecast error measures, including the root mean squared error (RMSE) and mean absolute error (MAE), together with the Diebold–Mariano test of predictive accuracy. The empirical results indicate that changes in the exchange rate, the conditional volatilities of the exchange rate and gold price, and daily index returns are positively associated with weekly stock market returns, whereas the empirical evidence indicates a negative relationship between changes in the gold price and stock returns. Furthermore, incorporating high-frequency daily information and short-term volatility into the MIDAS specification resulted in a statistically significant reduction in out-of-sample forecast errors, as confirmed by the Diebold–Mariano test. The findings demonstrate the effectiveness of mixed-frequency models in extracting latent information from daily data to improve forecasting accuracy and risk management in the capital market.

Keywords: MIDAS model, Tehran Stock Exchange Total Index return, exchange rate, global gold price, global oil price, GARCH, capital market return forecasting.

1. Introduction

Forecasting stock market returns remains one of the most persistent and technically challenging problems in financial economics, investment management, and quantitative risk analysis. Accurate forecasts of market returns can improve asset allocation, portfolio rebalancing, risk budgeting, hedging, and strategic investment decisions, while also assisting policymakers in understanding the transmission of macroeconomic shocks into financial markets. The relevance of this issue extends beyond the behavior of investors because stock markets contribute to capital formation, liquidity provision, and the allocation of financial resources within the broader economy. Evidence from international markets shows that stock market development and capitalization can interact with financial-sector growth and economic performance, while stock returns may also be connected with broader distributional and macroeconomic outcomes

[1-3]. For this reason, improving the accuracy of stock return forecasting is not merely a statistical exercise; it has practical implications for financial stability, investment management, and the assessment of market risk.

Despite its importance, forecasting stock returns is difficult because financial markets are characterized by nonlinearity, structural change, volatility clustering, regime dependence, behavioral responses, and sensitivity to a wide range of domestic and international information. Short-horizon return dynamics can reflect both persistent economic factors and rapidly evolving market expectations. Recent studies have therefore increasingly moved beyond purely linear and single-frequency forecasting approaches toward nonlinear, machine-learning, deep-learning, and mixed-frequency frameworks [4-6]. The growing diversity of forecasting methods reflects the fact that no single class of models can fully capture all features of financial time series. Classical time-series models remain useful because of their interpretability and parsimonious structure, but more recent approaches attempt to exploit nonlinearities, complex temporal dependence, high-dimensional information, and interactions across multiple frequencies.

The rapid development of computational methods has considerably expanded the range of techniques available for financial forecasting. Deep neural networks and related artificial-intelligence methods have been applied to return prediction, regime classification, corporate credit assessment, and index forecasting, particularly where nonlinearities and complex temporal patterns are expected [7-9]. In the Tehran Stock Exchange, deep-learning and hybrid neural-network approaches have been employed to model index behavior, identify regime changes, and extract multiscale temporal features [8, 10]. Neural-network forecasting has also been extended through nonlinear autoregressive architectures such as NARX models, which have been used to forecast the TSE Total Index by exploiting nonlinear temporal dependence [11]. Internationally, forecasting studies have likewise employed ensemble machine-learning models, ARIMAX models, deep neural networks, and Prophet-type approaches, illustrating the broad methodological shift toward flexible prediction systems [5, 6, 12].

Although these approaches have improved predictive flexibility, they do not eliminate a fundamental characteristic of financial and macroeconomic data: economically relevant variables are observed at different sampling frequencies. Stock prices and returns may be available daily or intraday, whereas macroeconomic indicators may be released weekly, monthly, or quarterly. Even among market-based variables, daily information can be aggregated into lower-frequency target variables, such as weekly or monthly stock returns. Conventional forecasting methods often require all variables to be transformed to a common frequency before estimation. Such temporal aggregation can discard intra-period information, smooth short-lived shocks, and obscure the timing of market responses. The development of mixed-frequency methods has therefore been especially important because these models allow high-frequency information to be incorporated directly when explaining or forecasting a lower-frequency variable [4, 13].

Mixed Data Sampling, or MIDAS, regression is particularly useful in this context because it allows a low-frequency dependent variable to be related parsimoniously to multiple lags of high-frequency predictors through parameterized weighting functions. Instead of estimating a separate unrestricted coefficient for every daily lag, MIDAS compresses the distributed-lag structure into a small number of parameters. This feature reduces parameter proliferation while retaining information contained in high-frequency observations. Such an approach is highly relevant for stock return forecasting, where recent daily changes in exchange rates, commodity prices, market returns, and volatility may collectively influence the subsequent weekly market outcome. Recent research has demonstrated the usefulness of mixed-frequency information in forecasting applications, including nowcasting and risk prediction, particularly when the high-frequency predictors contain information that would otherwise be lost

through aggregation [13, 14]. In the Iranian context, comparative evidence has also indicated that nonlinear MIDAS specifications may offer advantages over conventional ARIMA-type models in forecasting Tehran stock market behavior [15].

A further reason for incorporating daily information into return forecasting is that financial markets respond rapidly to macroeconomic and cross-market signals. Exchange-rate movements are particularly important in emerging markets because they may affect inflation expectations, import costs, export revenues, replacement values of assets, and the profitability of firms with foreign-currency exposure. Consequently, exchange-rate changes can influence both expected cash flows and discount rates. Empirical studies of the Tehran Stock Exchange have documented meaningful relationships among exchange rates, oil prices, gold prices, and stock market conditions, with these relationships potentially varying across bullish and bearish regimes [16]. More broadly, international evidence also supports the relevance of macroeconomic conditions for stock market performance, although the magnitude and direction of these effects can differ across economies and periods [17, 18]. These findings suggest that forecasting weekly stock returns may benefit from models that incorporate daily changes in major macro-financial variables rather than relying exclusively on historical stock returns.

Gold and oil prices constitute two additional channels through which global market conditions may affect equity returns. Gold is widely regarded as an alternative investment and, in some circumstances, a safe-haven or defensive asset. Changes in gold prices may therefore reflect shifts in risk perception, inflation expectations, or investor portfolio preferences. Oil prices, by contrast, can affect corporate profitability, production costs, government revenues, external balances, and economic expectations, particularly in oil-producing economies. Research on oil and energy markets has shown that return dynamics and abnormal returns may display time-varying frequency structures and nonlinear behavior [19]. Studies of crude-oil volatility further demonstrate the importance of explicitly modeling conditional variance when analyzing commodity-price dynamics [20]. In this respect, incorporating high-frequency oil and gold information into equity forecasting models can provide a richer representation of the cross-market information set faced by investors.

Volatility itself is another critical source of predictive information. Financial returns rarely exhibit constant variance over time. Instead, periods of tranquility tend to be followed by other low-volatility periods, while turbulent episodes are often followed by further turbulence. This phenomenon of volatility clustering has motivated the widespread use of ARCH- and GARCH-family models in empirical finance. GARCH models summarize the effect of new shocks and past conditional variance on current volatility and remain fundamental tools in financial risk measurement and forecasting [21, 22]. More broadly, the estimation and management of time-varying market risk constitute central components of quantitative risk management [23]. In the Iranian stock market, evidence also indicates that changes in trading rules and permissible price fluctuation ranges can affect realized daily volatility, emphasizing the importance of explicitly modeling volatility dynamics rather than treating risk as constant over time [24].

The predictive role of volatility is especially relevant when high-frequency conditional volatility estimates are combined with a lower-frequency forecasting target. Exchange-rate volatility may affect stock returns through uncertainty regarding firms' costs, foreign-currency revenues, inflation, and monetary conditions. Similarly, volatility in gold prices may capture changes in global uncertainty and portfolio substitution between safe-haven assets and equities. Incorporating GARCH-derived daily volatility measures into a MIDAS framework therefore offers a way to combine information on both the direction of market movements and the intensity of financial

uncertainty. Such integration is consistent with the broader movement in forecasting research toward richer information sets and models capable of processing heterogeneous temporal structures [4, 14].

Daily stock market information itself may also improve forecasts of weekly returns. High-frequency equity returns contain information about short-term momentum, reversal, market sentiment, and the gradual incorporation of information into prices. Research on weekly stock-return forecasting has shown that short-horizon information can retain predictive value even when evaluated against market-efficiency considerations [5]. Weekly options indicators have also been shown to contain useful information for short-term equity return prediction, further illustrating that market variables observed at relatively high frequencies can contribute to forecasting at weekly horizons [25]. In the Tehran Stock Exchange, calendar and day-specific characteristics have likewise been associated with stock market performance, suggesting that high-frequency patterns should not automatically be assumed to disappear when returns are aggregated to longer horizons [26]. For these reasons, incorporating daily TSE Total Index returns into a weekly MIDAS specification may capture information that would be lost if only weekly observations were considered.

The usefulness of richer forecasting frameworks is also supported by the broader literature on feature extraction and financial prediction. Financial data often contain noisy and redundant information, and considerable research has therefore focused on extracting the most informative temporal features before prediction [27]. Portfolio decision systems have similarly attempted to combine advanced analytical techniques with financial-market information in order to improve asset-selection and allocation decisions [28]. Other studies have examined investment risk across multiple time horizons using techniques such as wavelet transformations, highlighting the importance of scale and frequency in financial behavior [29]. Together, these studies reinforce the methodological argument that market dynamics should be examined across temporal scales rather than exclusively within a single fixed frequency.

The forecasting problem is particularly relevant in the Tehran Stock Exchange because the Iranian capital market is exposed to pronounced macroeconomic uncertainty, exchange-rate fluctuations, political developments, commodity-price movements, and rapidly changing investor expectations. Political uncertainty has been shown to influence stock market volatility in Iran, especially when international developments are taken into account [30]. Risk-related disclosures can also affect market reactions, demonstrating that investors respond to changing information regarding uncertainty and firm-specific risk [31]. More recent evidence indicates that returns in alternative asset classes such as cryptocurrencies may also be associated with the behavior of the TSE Total Index, further emphasizing that the Iranian stock market operates within an increasingly interconnected financial environment [32]. These characteristics make the TSE an appropriate setting for evaluating forecasting models that combine multiple sources of high-frequency financial information.

The complexity of Iranian market behavior has led researchers to adopt a wide range of forecasting techniques, from deep neural networks to hybrid architectures and nonlinear models. Nevertheless, much of the existing domestic research has focused on either single-frequency forecasting, nonlinear prediction, classification, or specific determinants of market behavior. The simultaneous integration of daily macro-financial changes, GARCH-derived conditional volatility, and daily stock index returns within a parsimonious weekly MIDAS framework remains comparatively underexplored. This gap is important because each information category captures a different dimension of market behavior: macro-financial variables reflect changes in external economic conditions, conditional volatility captures uncertainty and risk persistence, and daily index returns summarize short-run endogenous stock-market dynamics.

The importance of evaluating such models should also be judged on the basis of genuine forecasting performance rather than in-sample fit alone. Models with higher explanatory power do not necessarily generate more accurate forecasts when applied to new observations. Out-of-sample evaluation is therefore essential for assessing whether additional variables and model complexity translate into practically useful predictive gains. Recent financial forecasting studies increasingly emphasize this distinction by comparing alternative models using formal forecast-error measures and external validation procedures [6, 33]. This concern is especially important in financial markets, where structural instability and overfitting can cause a model that performs well historically to perform poorly prospectively. Accordingly, comparisons based on root mean squared error, mean absolute error, and statistical tests of predictive accuracy provide more convincing evidence regarding the practical value of mixed-frequency models.

From a theoretical perspective, the proposed forecasting framework therefore combines several complementary ideas. First, weekly stock returns may respond to short-run changes in macro-financial variables such as the exchange rate, gold price, and oil price. Second, the intensity of uncertainty in foreign-exchange and gold markets may contain incremental predictive information beyond directional price changes. Third, daily stock returns may summarize recent market information that has not yet been fully reflected in weekly aggregates. Fourth, a parameterized MIDAS lag structure can preserve the information contained in multiple daily observations while avoiding the excessive dimensionality that would arise from unrestricted distributed-lag models. This combination is consistent with current developments in financial forecasting, which increasingly emphasize nonlinear dynamics, heterogeneous information frequencies, and rigorous out-of-sample validation [4, 13].

Accordingly, the aim of this study was to evaluate the out-of-sample forecasting performance of a Beta-weighted MIDAS regression model for weekly Tehran Stock Exchange Total Index returns by jointly incorporating daily changes in the exchange rate, global gold and oil prices, GARCH-based conditional volatility measures, and daily TSE Total Index returns.

2. Methods and Materials

This study was applied in terms of its objective because its findings are intended to improve forecasting, investment analysis, and risk assessment in the capital market. In terms of research design and analytical approach, it was a quantitative econometric study based on financial time-series data. The principal methodological contribution of the study was the development of an integrated mixed-frequency forecasting framework for the weekly return of the Tehran Stock Exchange (TSE) Total Index in which daily information on selected macroeconomic and financial variables, daily conditional volatility measures obtained from GARCH models, and the daily return of the TSE Total Index were incorporated simultaneously into a Mixed Data Sampling (MIDAS) regression framework. The use of mixed-frequency modeling was particularly appropriate because economic and financial variables are commonly observed at different frequencies, and conventional temporal aggregation may discard potentially useful within-period information. MIDAS regression provides a parsimonious framework for exploiting higher-frequency information when forecasting a lower-frequency dependent variable without requiring all series to be converted to a common frequency (Ghysels et al., 2007; Setiawan et al., 2025). The dependent variable was the weekly return of the TSE Total Index, while the explanatory variables consisted of daily changes in the exchange rate, daily changes in the global gold price, daily changes in the global oil price, daily exchange-rate volatility, daily gold-price volatility, and the daily return of the TSE Total Index. Accordingly, the

empirical design made it possible to examine whether macro-financial information observed at the daily frequency contained incremental predictive information for subsequent weekly stock market returns.

The statistical sample comprised all valid and available observations for the TSE Total Index and the selected macroeconomic and financial variables from March 2016 to March 2025. This period was selected to provide sufficiently broad coverage of developments in the Iranian capital market while maintaining adequate availability and continuity of the required daily financial data. The database contained approximately 2,000 observations for variables measured at the daily frequency and approximately 400 observations for the weekly dependent variable. The exact number of observations used in each model was determined after calendar alignment across the series, removal of missing or unusable observations, construction of the required transformations, and application of the model-specific lag structure. Because the study relied entirely on secondary archival data, no random sampling procedure was employed. Instead, all available and valid observations within the defined study period were retained after data preparation and screening. This full-period approach was considered appropriate for time-series forecasting because excluding valid observations through random sampling would reduce the temporal information available for model estimation and could disrupt the sequential dependence inherent in financial data.

To assess genuine predictive performance rather than merely in-sample goodness of fit, the observations were divided into in-sample and out-of-sample segments. The in-sample portion was used to estimate the regression coefficients and the parameters governing the MIDAS weighting functions, whereas the out-of-sample portion was reserved exclusively for forecast evaluation and was not used in the initial parameter estimation. Out-of-sample forecasts were generated through a recursive expanding-window procedure. Under this approach, an initial estimation sample was specified, the model was estimated, and a forecast for the subsequent observation was produced. The newly observed value was then incorporated into the estimation sample, the model was re-estimated, and the procedure was repeated sequentially throughout the forecasting period. Consequently, the estimation window expanded over time while all previously available observations were retained. This design reflects the information set that would have been available to a forecaster at each point in time and therefore provides a more realistic assessment of practical forecasting performance.

The data collection procedure was based on secondary financial and macroeconomic time-series records. The principal market variable was the TSE Total Index, which was used as the representative indicator of aggregate stock market performance in Iran. Daily observations were collected for the TSE Total Index as well as for the exchange rate, global gold price, and global oil price. These data were subsequently aligned according to the trading calendar to account for differences in trading days and market closures. The weekly return of the TSE Total Index was constructed as the low-frequency dependent variable, while information derived from the daily series constituted the high-frequency explanatory component of the MIDAS models. Daily changes in the exchange rate, gold price, and oil price were used to capture short-run movements in relevant macro-financial conditions. In addition, the daily return of the TSE Total Index was incorporated into the extended MIDAS specification to determine whether high-frequency information from the stock market itself contributed additional forecasting power beyond that contained in external macroeconomic variables.

A second category of explanatory information consisted of conditional volatility measures obtained from daily exchange-rate and gold-price series. These volatility measures were not directly observed variables but were estimated using separate Generalized Autoregressive Conditional Heteroskedasticity models of order GARCH(1,1). The GARCH framework was employed because financial return series frequently exhibit volatility clustering, implying that periods of high volatility tend to be followed by further periods of high volatility and

periods of low volatility tend to persist. For the exchange-rate series, the conditional mean and conditional variance processes were specified as

$$\begin{aligned} r_t^{EX} &= \mu + \varepsilon_t, \quad \varepsilon_t \mid \Omega_{t-1} \sim N(0, h_t), \\ h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}, \end{aligned}$$

where r_t^{EX} denotes the daily exchange-rate return or change series used in the volatility model, μ is the conditional mean, ε_t is the innovation at time t , Ω_{t-1} denotes the information set available through time $t - 1$, and h_t represents the conditional variance of the exchange rate. The parameters ω , α , and β respectively capture the long-run variance component, the short-run impact of new shocks, and the persistence of previous conditional volatility.

Similarly, conditional volatility in the global gold-price series was estimated as

$$\begin{aligned} r_t^{GOLD} &= \mu + v_t, \quad v_t \mid \Omega_{t-1} \sim N(0, g_t), \\ g_t &= \omega + \alpha v_{t-1}^2 + \beta g_{t-1}, \end{aligned}$$

where r_t^{GOLD} denotes the daily gold-price return or change series, v_t is its innovation, and g_t denotes the corresponding conditional variance. The estimated daily series h_t and g_t were subsequently treated as volatility indicators and entered the MIDAS framework as $VOL_EX_t^{(d)}$ and $VOL_GOLD_t^{(d)}$, respectively. This two-stage procedure enabled the study to examine not only the predictive content of changes in macro-financial variables but also the contribution of short-run uncertainty and volatility dynamics to forecasts of weekly stock market returns.

Data analysis was conducted primarily using MIDAS regression, a mixed-frequency econometric technique designed to relate a low-frequency dependent variable to explanatory variables observed at a higher frequency. The general MIDAS model can be expressed as

$$Y_t = \alpha + \beta \sum_{k=0}^K w_k(\theta) x_{t-k/m} + \varepsilon_t,$$

where Y_t is the low-frequency dependent variable, $x_{t-k/m}$ represents the high-frequency explanatory variable, m is the number of high-frequency observations contained within each low-frequency period, K is the maximum number of high-frequency lags, $w_k(\theta)$ is a parametric weighting function governed by the parameter vector θ , α is the intercept, β is the slope coefficient associated with the weighted high-frequency information, and ε_t is the regression error term. The principal advantage of this specification is that it does not require estimation of an unrestricted coefficient for every individual daily lag. Instead, a relatively small number of parameters determine the entire lag-weighting profile, thereby reducing parameter proliferation and improving model parsimony (Al-Shubiri, 2021).

Two commonly used MIDAS lag-weighting structures are the Almon polynomial and the Beta polynomial. The normalized Almon polynomial weighting function can be written as

$$w_k(\theta) = \frac{\sum_{i=0}^p \theta_i k^i}{\sum_{k=0}^K \sum_{i=0}^p \theta_i k^i},$$

where p denotes the polynomial degree and the parameters θ_i determine the shape of the lag distribution. This formulation permits the effects of high-frequency observations to change gradually and nonlinearly across lags. However, the primary analyses in the present study employed the normalized Beta polynomial weighting function because of its flexibility in representing increasing, decreasing, hump-shaped, or otherwise nonlinear patterns of influence across daily lags. The Beta weighting function was defined as

$$w_k(\theta_1, \theta_2) = \frac{(k/K)^{\theta_1-1} (1 - k/K)^{\theta_2-1}}{\sum_{k=0}^K (k/K)^{\theta_1-1} (1 - k/K)^{\theta_2-1}}, \theta_1, \theta_2 > 0.$$

The normalization ensures that the lag weights sum to one. Consequently, the parameters θ_1 and θ_2 determine the relative importance assigned to more recent versus more distant daily observations without requiring a separate freely estimated coefficient for every lag. In the present study, a maximum lag length of 22 trading days was initially adopted for the daily predictors. This horizon approximately corresponds to one trading month and was considered sufficiently long to capture delayed short-term effects of daily macro-financial information on weekly equity returns while maintaining a parsimonious specification. The suitability of the lag structure was additionally assessed on the basis of model information criteria and out-of-sample forecasting performance.

The MIDAS parameters were estimated using nonlinear least squares. The estimator was defined as

$$\min_{\alpha, \beta, \theta} \sum_{t=1}^T \left(Y_t - \alpha - \beta \sum_{k=0}^K w_k(\theta) x_{t-k/m} \right)^2.$$

Accordingly, the estimated parameters $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\theta}$ were those values that minimized the sum of squared residuals. Nonlinear least squares is required because the parameters of the weighting function enter the regression equation nonlinearly. The estimated weighting parameters were used to determine the contribution of individual daily lags to the weekly forecast. The GARCH(1,1) models used to construct the conditional volatility variables were estimated separately before the resulting conditional variance series were incorporated into the MIDAS models.

The first empirical specification examined whether daily macroeconomic information improved the prediction of weekly TSE Total Index returns. The model was specified as

$$R_t^{(w)} = \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \varepsilon_t,$$

where $R_t^{(w)}$ denotes the weekly return of the TSE Total Index, $EX_{t-j/m}^{(d)}$, $GOLD_{t-j/m}^{(d)}$, and $OIL_{t-j/m}^{(d)}$ denote daily exchange-rate, gold-price, and oil-price information at the corresponding high-frequency lags, respectively, and $B(j; \theta)$ represents the Beta polynomial lag-weighting function. This specification was used to test whether information contained in daily macro-financial variables reduced forecast error relative to less information-intensive forecasting specifications.

The second empirical specification examined whether daily conditional volatility in the exchange rate and global gold price provided incremental predictive information. After obtaining the volatility series from the GARCH(1,1) models, they were incorporated into the MIDAS equation as follows:

$$\begin{aligned}
 R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\
 & + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \sum_{j=1}^{K_4} \lambda_j B(j; \theta_4) VOL_EX_{t-j/m}^{(d)} \\
 & + \sum_{j=1}^{K_5} \eta_j B(j; \theta_5) VOL_GOLD_{t-j/m}^{(d)} + \varepsilon_t.
 \end{aligned}$$

In this equation, $VOL_EX^{(d)}$ denotes daily exchange-rate conditional volatility and $VOL_GOLD^{(d)}$ denotes daily conditional volatility in the gold-price series, both derived from the preceding GARCH estimations. Comparison of this specification with the macroeconomic-variable MIDAS model made it possible to assess whether incorporating high-frequency measures of financial uncertainty generated additional improvements in weekly return forecasts.

The third empirical analysis evaluated the incremental forecasting contribution of the daily TSE Total Index return. The baseline specification without daily index returns was

$$R_t^{(w)} = \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \varepsilon_t.$$

The corresponding extended model was specified as

$$\begin{aligned}
 R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\
 & + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \sum_{j=1}^{K_6} \rho_j B(j; \theta_6) R_{t-j/m}^{(d)} + \varepsilon_t,
 \end{aligned}$$

where $R_{t-j/m}^{(d)}$ denotes the daily return of the TSE Total Index. The forecasting performance of the extended specification was compared with that of the baseline model to determine whether daily stock market information significantly improved the accuracy of forecasts for weekly index returns.

Forecast accuracy was evaluated using out-of-sample forecast errors obtained from the recursive expanding-window procedure. Root mean squared error (RMSE) and mean absolute error (MAE) were used as the principal loss measures. They were computed as

$$RMSE = \sqrt{\frac{1}{H} \sum_{t=1}^H (R_t^{(w)} - \hat{R}_t^{(w)})^2},$$

and

$$MAE = \frac{1}{H} \sum_{t=1}^H |R_t^{(w)} - \hat{R}_t^{(w)}|,$$

where H denotes the number of observations in the out-of-sample forecasting period, $R_t^{(w)}$ is the realized weekly return, and $\hat{R}_t^{(w)}$ is the corresponding model forecast. Lower RMSE and MAE values indicated greater predictive

accuracy. Because numerical differences in forecast error measures alone do not establish whether one model forecasts significantly better than another, pairwise differences in predictive accuracy were additionally evaluated using the Diebold–Mariano test. The test was based on the differential between the forecast losses of two competing models,

$$d_t = L(e_{1t}) - L(e_{2t}),$$

with the null hypothesis

$$H_0: E(d_t) = 0,$$

indicating equal predictive accuracy. A statistically significant Diebold–Mariano statistic was interpreted as evidence that the competing specifications differed significantly in out-of-sample forecasting performance. The combined use of RMSE, MAE, and the Diebold–Mariano test therefore allowed the study to determine whether the inclusion of daily macroeconomic variables, GARCH-based conditional volatility measures, and daily TSE Total Index returns produced economically and statistically meaningful improvements in the prediction of weekly stock market returns.

3. Findings and Results

The empirical analysis was conducted in several stages, beginning with an examination of the characteristics of the study variables, followed by stationarity and conditional heteroskedasticity tests, estimation of the GARCH(1,1) models, estimation of alternative MIDAS specifications, evaluation of out-of-sample forecasting accuracy, and diagnostic assessment of the final forecasting model. The dependent variable was the weekly return of the Tehran Stock Exchange (TSE) Total Index, whereas the explanatory information was observed at the daily frequency and included the daily return of the TSE Total Index, exchange rate, global gold price, global oil price, and the conditional volatility of the exchange rate and gold price. The use of daily observations was particularly important because such data preserve short-run movements, temporary shocks, and rapid market reactions that may be lost through conventional temporal aggregation.

Table 1. Study Variables

Variable	Symbol	Role	Frequency
Weekly return of the TSE Total Index	R_t^W	Dependent	Weekly
Daily return of the TSE Total Index	R_t^D	Independent	Daily
Exchange rate	EX_t^D	Independent	Daily
Global gold price	$GOLD_t^D$	Independent	Daily
Global oil price	OIL_t^D	Independent	Daily
Exchange-rate volatility	$VOL_EX_t^D$	Derived independent	Daily
Gold-price volatility	$VOL_GOLD_t^D$	Derived independent	Daily

The descriptive statistics provide an initial picture of the central tendency, dispersion, asymmetry, and tail behavior of the daily series. As shown in Table 2, the daily return of the TSE Total Index had a mean of 0.12 and a standard deviation of 1.84, indicating substantial short-term variation in stock market returns. Its values ranged from −5.72 to 6.11. Positive skewness of 0.31 indicates a slightly longer right tail, while kurtosis of 4.87 exceeds the normal-distribution benchmark and is consistent with relatively heavy tails and the occurrence of unusually large

return movements. Such features are common in financial time series and indicate that large shocks occurred during the study period.

Table 2. Descriptive Statistics of Daily Variables

Variable	Mean	Median	SD	Maximum	Minimum	Kurtosis	Skewness
R_t^D	0.12	0.09	1.84	6.11	-5.72	4.87	0.31
EX_t^D	58,120	57,980	842.5	60,350	56,210	3.94	0.18
$GOLD_t^D$	2,418	2,412	26.4	2,479	2,358	3.61	0.27
OIL_t^D	79.6	79.4	2.94	85.2	73.1	4.12	0.44
$VOL_EX_t^D$	1.21	1.08	0.67	4.18	0.22	5.43	1.06
$VOL_GOLD_t^D$	0.84	0.79	0.41	2.73	0.12	4.96	0.98

The daily exchange rate had a mean of 58,120 and a standard deviation of 842.5. Its positive skewness and kurtosis close to 4 indicate that its empirical distribution was not fully normal and that several relatively large upward movements occurred. The global gold price had a mean of 2,418 and a standard deviation of 26.4, with a narrower range than the exchange rate and stock return series, suggesting comparatively greater stability over the study period. Nevertheless, its positive skewness and kurtosis above 3 indicate asymmetric movements and the possibility of abnormal changes during particular periods. The global oil price had a mean of 79.6 and a standard deviation of 2.94. Its positive skewness of 0.44 indicates that relatively large positive movements occurred somewhat more frequently than large negative movements, while kurtosis of 4.12 suggests heavier tails than under normality.

The GARCH-derived exchange-rate and gold-price volatility series had means of 1.21 and 0.84, respectively. Both variables displayed pronounced positive skewness and kurtosis greater than 4. Exchange-rate volatility had skewness of 1.06 and kurtosis of 5.43, while gold-price volatility had skewness of 0.98 and kurtosis of 4.96. These characteristics are consistent with episodic increases in financial uncertainty and volatility clustering. The descriptive evidence therefore provided an initial empirical rationale for explicitly modeling time-varying conditional variance.

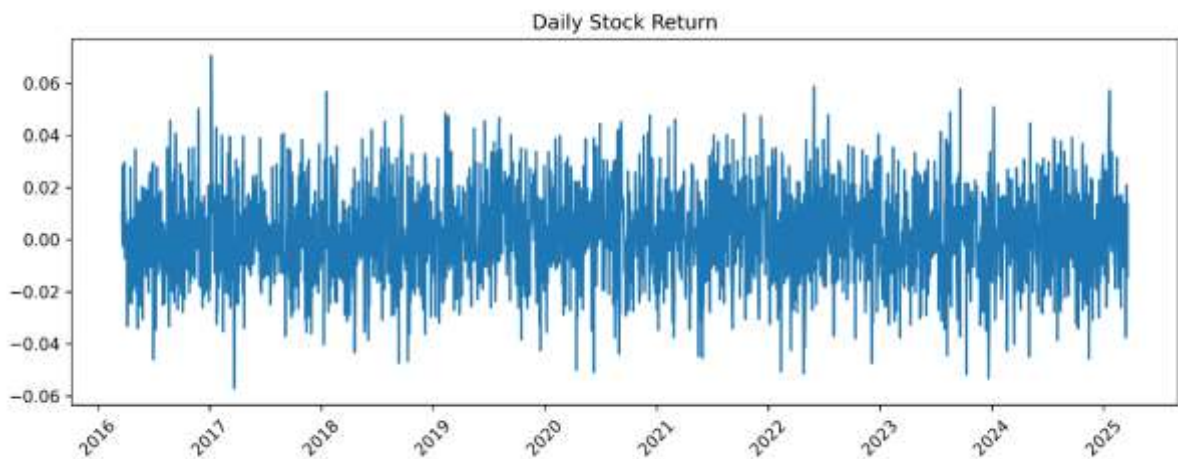


Figure 1. Trend of Daily Stock Returns

Figure 1 presents daily stock returns over the 2016–2025 study period. Periods of pronounced fluctuations are interspersed with relatively tranquil intervals, a pattern consistent with volatility clustering. This behavior is a common characteristic of financial time series and provides further justification for the use of GARCH-family models when extracting conditional volatility measures.

Before estimating the forecasting models, the stationarity properties of the series were examined using the Augmented Dickey–Fuller (ADF) unit-root test. The results reported in Table 3 indicate that the daily TSE Total Index return and the two GARCH-derived conditional volatility series were stationary in levels, or $I(0)$. In contrast, the daily exchange rate, global gold price, and global oil price were nonstationary in levels. After first differencing, however, the unit-root null hypothesis was rejected at the 1% significance level for all three variables. Consequently, first differences rather than levels of the nonstationary macro-financial variables were used in the MIDAS specifications to reduce the risk of spurious regression.

Table 3. Augmented Dickey–Fuller Stationarity Test Results

Variable	Form	ADF Statistic	p-value	Stationarity Result
Daily TSE return, R_t^D	Level	−9.42	0.0000	Stationary, $I(0)$
Exchange rate, EX_t^D	Level	−1.87	0.3431	Nonstationary
ΔEX_t^D	First difference	−11.35	0.0000	Stationary after first differencing
Gold price, $GOLD_t^D$	Level	−2.11	0.2394	Nonstationary
$\Delta GOLD_t^D$	First difference	−10.82	0.0000	Stationary after first differencing
Oil price, OIL_t^D	Level	−1.95	0.3078	Nonstationary
ΔOIL_t^D	First difference	−12.14	0.0000	Stationary after first differencing
Exchange-rate volatility, $VOL_EX_t^D$	Level	−7.61	0.0000	Stationary, $I(0)$
Gold-price volatility, $VOL_GOLD_t^D$	Level	−6.94	0.0000	Stationary, $I(0)$

The presence of conditional heteroskedasticity was subsequently examined using ARCH-LM tests for the daily exchange-rate and gold return series. For the exchange rate, the LM statistics at lags 1, 2, and 3 were 18.42, 21.57, and 19.88, respectively, with p-values of 0.0000 in all cases. Thus, the null hypothesis of no ARCH effect was rejected for all three lag orders. For the gold return series, the corresponding LM statistics were 16.33, 17.90, and 15.76, with p-values of 0.0000, 0.0000, and 0.0001, respectively. These results likewise rejected the null hypothesis of homoskedasticity. Accordingly, both financial series exhibited significant conditional heteroskedasticity, implying that past shocks affected current volatility and that tranquil and turbulent periods tended to occur in clusters. The evidence therefore supported the use of GARCH models for estimating conditional volatility.

After confirmation of ARCH effects, GARCH(1,1) models were estimated separately for the exchange-rate and gold-price series. In the recursive out-of-sample forecasting framework, the GARCH parameters at each forecasting origin were estimated using only information available up to that point, thereby preventing future information from entering the estimated volatility measures. Table 4 shows that all GARCH parameters were statistically significant at the 5% level for both series.

Table 4. GARCH(1,1) Estimation Results for the Exchange Rate and Global Gold Price

Series	Parameter	Coefficient	t Statistic	p-value	Result
Exchange rate	ω	0.021	2.31	0.0208	Significant
Exchange rate	α	0.164	3.42	0.0006	Significant
Exchange rate	β	0.781	10.18	0.0000	Significant
Gold price	ω	0.017	2.07	0.0384	Significant
Gold price	α	0.142	3.09	0.0020	Significant
Gold price	β	0.806	11.44	0.0000	Significant

For the exchange-rate model, the ARCH coefficient was 0.164 ($p = 0.0006$), indicating that new market shocks had a statistically significant effect on current volatility. The GARCH coefficient was substantially larger at 0.781 ($p < 0.001$), showing strong persistence from previous volatility. The sum of the ARCH and GARCH coefficients

was 0.945, which was below unity. Thus, the estimated conditional variance process was stable, although volatility shocks were highly persistent and dissipated only gradually over time. These findings indicate that the GARCH(1,1) specification adequately captured the dynamic behavior of exchange-rate volatility for subsequent incorporation into the MIDAS framework.

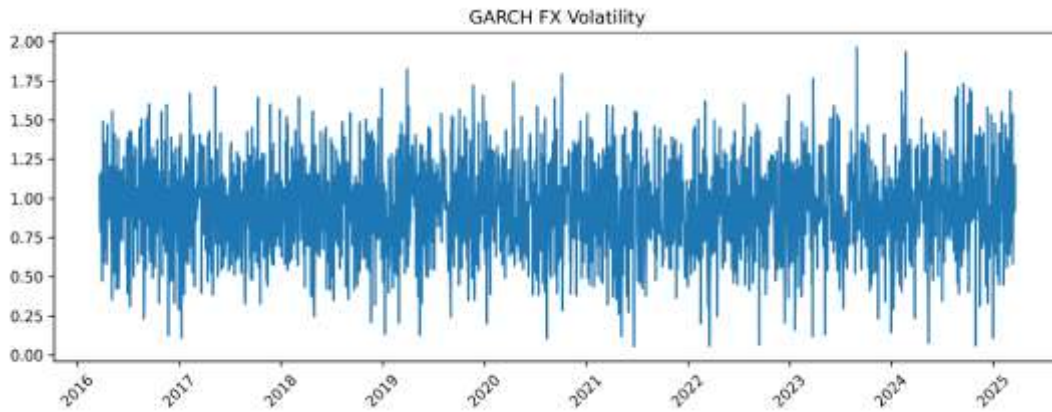


Figure 2. GARCH Conditional Volatility of the Exchange Rate

Figure 2 displays the estimated conditional variance of the exchange-rate series. Large peaks represent periods of heightened uncertainty and market risk, whereas lower values correspond to periods of relative stability. The recurrent appearance of high-volatility episodes confirms the time-varying nature of exchange-rate risk.

For the global gold-price model, the ARCH coefficient was 0.142 ($p = 0.0020$) and the GARCH coefficient was 0.806 ($p < 0.001$). The statistical significance of both parameters shows that current gold-price volatility was influenced by both new shocks and previous volatility. Their sum was 0.948, again below unity, indicating a stable but highly persistent conditional variance process. Although shocks increased volatility, their effects declined gradually over time and conditional variance tended to revert toward its longer-run level. The estimated conditional variance series was therefore retained as the daily gold-volatility indicator in the subsequent MIDAS models.

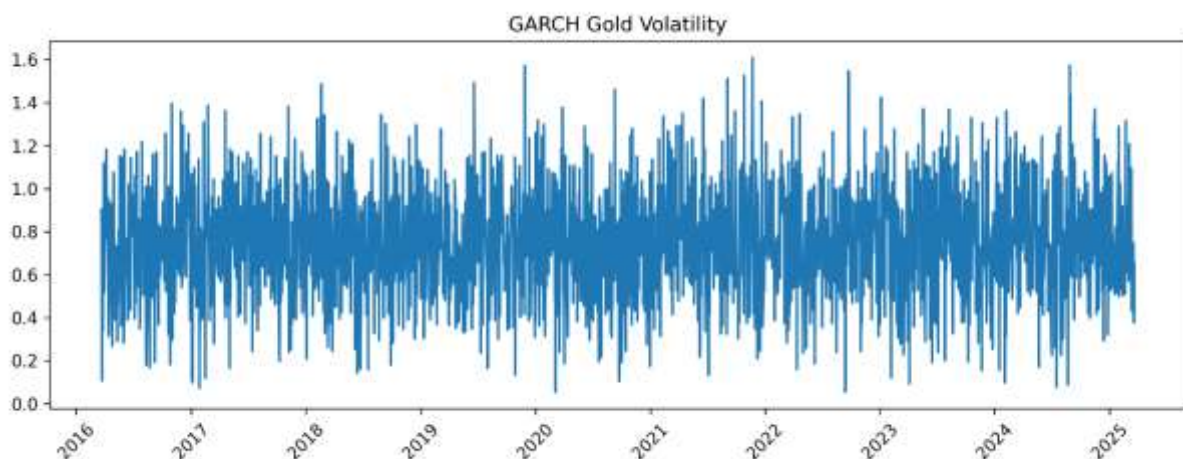


Figure 3. GARCH Conditional Volatility of the Global Gold Price

Figure 3 presents the estimated conditional volatility of the global gold-price series. The magnitude of volatility varied considerably over the observation period, with pronounced increases during particular intervals, indicating that economic and financial shocks generated temporary episodes of elevated uncertainty in the gold market.

The MIDAS analysis was then performed to assess the predictive contribution of high-frequency daily information to weekly TSE Total Index returns. The first specification included daily changes in the exchange rate, global gold price, and global oil price. Because the corresponding variables were nonstationary in levels, the empirical MIDAS models used their stationary first differences. As shown in Table 5, the exchange-rate coefficient was positive and statistically significant at the 5% level ($\beta = 0.287$, $p = 0.0046$), whereas the gold-price coefficient was negative and significant ($\beta = -0.194$, $p = 0.0348$). The oil-price coefficient was positive ($\beta = 0.132$) but had a p-value of 0.0591; accordingly, it did not reach the conventional 5% significance threshold, although it was marginally significant at the 10% level. Similarly, the intercept had a p-value of 0.0502 and should be interpreted as borderline rather than clearly significant at the 5% level.

Table 5. Results of the Baseline MIDAS Model

Variable/Indicator	Coefficient/Value	t Statistic	p-value
Intercept	0.214	1.96	0.0502
Exchange rate	0.287	2.84	0.0046
Gold price	-0.194	-2.11	0.0348
Oil price	0.132	1.89	0.0591
Weighting function	Beta	—	—
Daily lag length	22 trading days	—	—
θ_1	1.84	—	—
θ_2	3.27	—	—
Log likelihood	-286.41	—	—
AIC	2.97	—	—
BIC	3.14	—	—
R^2	0.43	—	—
Adjusted R^2	0.40	—	—
Effective observations	448	—	—

The positive exchange-rate coefficient indicates that, conditional on the other variables included in the model, increases in the exchange-rate measure were associated with higher weekly TSE Total Index returns. This pattern is compatible with mechanisms involving inflation expectations, nominal asset valuation, and the earnings of export-oriented firms; however, the estimated association should not be interpreted as establishing a causal effect. In contrast, the negative gold-price coefficient is consistent with a possible asset-substitution mechanism in which increased attractiveness of gold coincides with weaker stock-market returns. This interpretation is likewise associative rather than causal. The baseline model had an R^2 of 0.43 and an adjusted R^2 of 0.40. The reported AIC and BIC values were used for relative model comparison, whereas the primary criterion for evaluating forecasting usefulness remained out-of-sample predictive performance.

The second MIDAS specification augmented the baseline model with the conditional volatility of the exchange rate and gold price extracted from the GARCH(1,1) models. As reported in Table 6, both volatility measures provided statistically significant incremental information. Exchange-rate volatility had a positive coefficient of 0.209 ($p = 0.0030$), and gold-price volatility had a positive coefficient of 0.173 ($p = 0.0148$). The exchange-rate coefficient remained positive and statistically significant ($\beta = 0.241$, $p = 0.0087$), while the gold-price coefficient remained negative and significant ($\beta = -0.177$, $p = 0.0419$). The oil-price coefficient remained positive but was significant only at the 10% level ($p = 0.0764$) and therefore was not statistically significant at the conventional 5% level.

Table 6. Results of the MIDAS Model with GARCH-Based Conditional Volatility

Variable/Indicator	Coefficient/Value	t Statistic	p-value
Intercept	0.191	1.88	0.0604
Exchange rate	0.241	2.63	0.0087
Gold price	-0.177	-2.04	0.0419
Oil price	0.118	1.77	0.0764
Exchange-rate volatility	0.209	2.97	0.0030
Gold-price volatility	0.173	2.44	0.0148
Weighting function	Beta	—	—
Daily lag length	22 trading days	—	—
θ_1	1.81	—	—
θ_2	3.11	—	—
Log likelihood	-279.62	—	—
AIC	2.91	—	—
BIC	3.09	—	—
R^2	0.51	—	—
Adjusted R^2	0.48	—	—
Effective observations	448	—	—

The significance of both conditional volatility variables indicates that financial-market uncertainty contained predictive information beyond the information conveyed by movements in the macro-financial variables themselves. The R^2 increased from 0.43 in the baseline specification to 0.51, while the adjusted R^2 increased from 0.40 to 0.48. The log likelihood improved from -286.41 to -279.62, and the AIC and BIC declined from 2.97 and 3.14 to 2.91 and 3.09, respectively. The estimated Beta weighting parameters, $\theta_1 = 1.81$ and $\theta_2 = 3.11$, characterized the distribution of influence across the 22 daily lags. Although these in-sample indicators were consistent with improved model fit, the principal assessment of model performance was based on out-of-sample forecast errors and formal predictive-accuracy tests.

The third specification added the daily return of the TSE Total Index as an additional high-frequency explanatory variable. Table 7 shows that daily index return was positive and highly significant ($\beta = 0.263$, $p = 0.0008$), indicating that information contained in recent daily stock returns contributed significantly to the prediction of weekly returns. The exchange-rate coefficient remained positive and significant ($\beta = 0.229$, $p = 0.0102$), whereas the global gold-price coefficient remained negative and significant ($\beta = -0.168$, $p = 0.0478$). The global oil-price coefficient was positive but did not reach the 5% significance level ($\beta = 0.109$, $p = 0.0864$). The intercept was also not significant at the 5% level ($p = 0.0671$).

Table 7. Results of the MIDAS Model Including Daily TSE Total Index Returns

Variable/Indicator	Coefficient/Value	t Statistic	p-value
Intercept	0.182	1.83	0.0671
Exchange rate	0.229	2.57	0.0102
Gold price	-0.168	-1.98	0.0478
Oil price	0.109	1.71	0.0864
Daily TSE Total Index return	0.263	3.36	0.0008
Weighting function	Beta	—	—
Daily lag length	22 trading days	—	—
θ_1	1.76	—	—
θ_2	2.95	—	—
Log likelihood	-271.38	—	—
AIC	2.84	—	—

BIC	3.02	—	—
R^2	0.58	—	—
Adjusted R^2	0.55	—	—
Effective observations	448	—	—

The inclusion of daily index returns was accompanied by a further improvement in model fit. The log likelihood increased to -271.38 , while the AIC and BIC declined to 2.84 and 3.02 . The R^2 increased to 0.58 and the adjusted R^2 to 0.55 . These changes indicate that daily stock-market information contained additional explanatory content beyond that captured by exchange-rate, gold-price, and oil-price information. Nevertheless, because the central objective of the study concerned forecasting rather than in-sample explanation, these improvements were interpreted jointly with out-of-sample forecast-error measures and the Diebold–Mariano test rather than on the basis of R^2 alone.

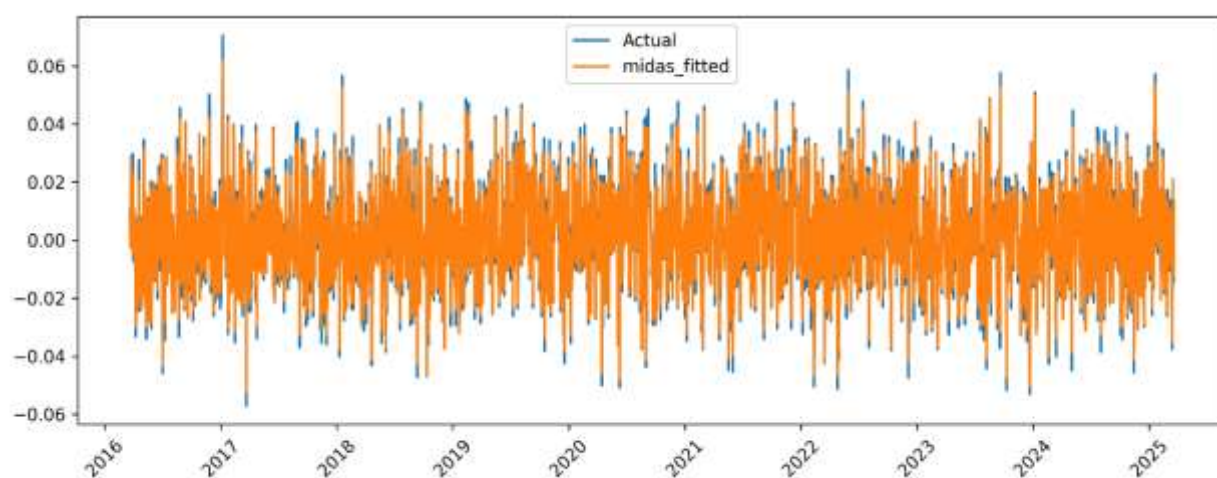


Figure 4. Comparison of Actual Weekly Returns and MIDAS Fitted Values

Figure 4 compares the realized weekly TSE Total Index returns with the corresponding fitted values from the MIDAS model. The general co-movement and relative proximity of the two series illustrate the extent to which the model reproduced the observed in-sample return dynamics.

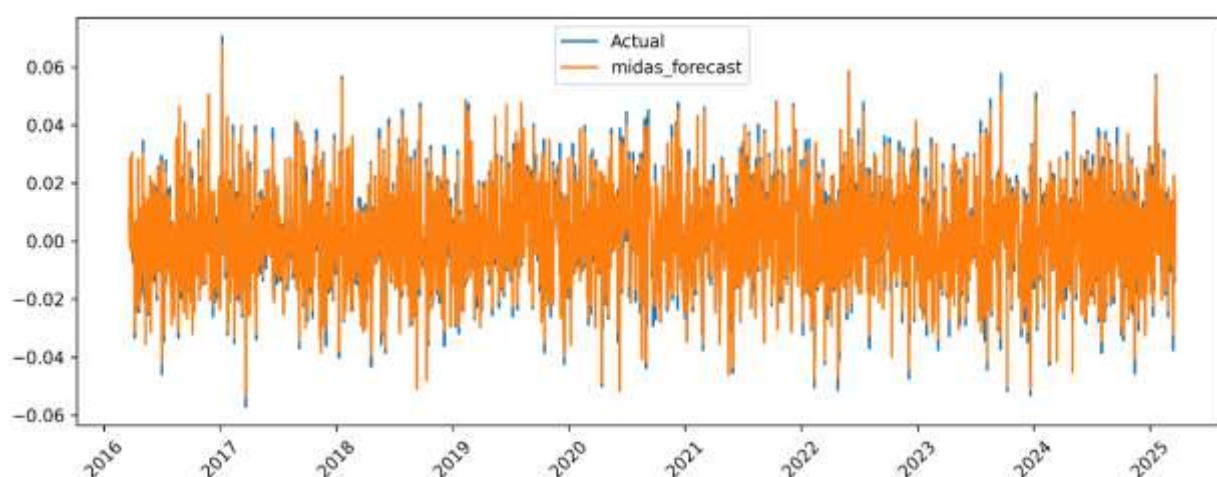


Figure 5. Comparison of Actual and Forecast Weekly TSE Total Index Returns

Figure 5 compares realized weekly returns with MIDAS out-of-sample forecasts. The distance between the two series at each forecasting point represents the magnitude of forecast error and provides a visual indication of periods in which predictive accuracy improved or deteriorated.

Out-of-sample forecasting performance was evaluated using RMSE and MAE as the principal criteria. MAPE was also reported as a supplementary measure, but it was not treated as the primary basis for model comparison because percentage errors can become unstable when realized returns are zero or close to zero. As reported in Table 8, forecast errors declined progressively as additional high-frequency information was introduced. The baseline MIDAS model had an RMSE of 2.41 and an MAE of 1.76. Adding GARCH-based volatility reduced these values to 2.18 and 1.59, respectively. The specification including daily TSE Total Index returns produced the lowest RMSE and MAE, at 2.06 and 1.47. MAPE similarly declined from 1.52 to 1.34 and then to 1.28.

Table 8. Out-of-Sample Forecasting Performance, Predictive-Accuracy Tests, and Final-Model Diagnostics

Analysis	Comparison/Model	Statistic/Measure	Value	p-value	Interpretation
Forecast accuracy	Baseline MIDAS	RMSE	2.41	—	Highest error among MIDAS specifications
Forecast accuracy	Baseline MIDAS	MAE	1.76	—	Higher error
Forecast accuracy	Baseline MIDAS	MAPE	1.52	—	Supplementary percentage-error measure
Forecast accuracy	MIDAS + GARCH volatility	RMSE	2.18	—	Lower error than baseline
Forecast accuracy	MIDAS + GARCH volatility	MAE	1.59	—	Lower error than baseline
Forecast accuracy	MIDAS + GARCH volatility	MAPE	1.34	—	Lower supplementary error
Forecast accuracy	MIDAS + daily index return	RMSE	2.06	—	Lowest RMSE
Forecast accuracy	MIDAS + daily index return	MAE	1.47	—	Lowest MAE
Forecast accuracy	MIDAS + daily index return	MAPE	1.28	—	Lowest supplementary MAPE
Diebold–Mariano test	Baseline vs. MIDAS + volatility	DM statistic	2.07	0.0389	Significant difference in predictive accuracy
Diebold–Mariano test	MIDAS + volatility vs. MIDAS + daily return	DM statistic	1.96	0.0498	Significant difference in predictive accuracy
Residual autocorrelation	Final MIDAS, Ljung–Box, lag 10	12.771	—	0.237	No significant residual autocorrelation
Residual normality	Final MIDAS, Jarque–Bera	2.132	—	0.344	Normality not rejected
Residual normality	Final MIDAS, Shapiro–Wilk	0.9960	—	0.276	Normality not rejected

The forecast-error results demonstrate that richer use of high-frequency information was associated with progressively smaller forecasting errors. In particular, incorporating conditional volatility reduced RMSE from 2.41 to 2.18 and MAE from 1.76 to 1.59. Adding daily index-return information further reduced RMSE to 2.06 and MAE to 1.47. For the final MIDAS specification, MAPE was 1.28%, compared with 1.52% for the baseline model. The simultaneous decline in RMSE and MAE is particularly important because RMSE places greater weight on relatively large forecast errors, whereas MAE reflects the average absolute forecasting deviation. Accordingly, improvement in both criteria indicates that the extended specification reduced both average errors and relatively large forecast misses. The results are consistent with the proposition that retaining intraperiod information from daily observations improves forecasts of weekly stock returns.

The statistical significance of these improvements was examined using the Diebold–Mariano test. Comparison of the baseline MIDAS model with the specification incorporating GARCH-based volatility produced a Diebold–Mariano statistic of 2.07 and a p-value of 0.0389, indicating a statistically significant difference in forecasting accuracy. Comparison of the volatility-augmented model with the specification incorporating daily index returns

produced a Diebold–Mariano statistic of 1.96 with a p-value of 0.0498. Thus, the observed reductions in forecast errors were not merely numerical differences; they were statistically significant at the 5% level. These findings support the predictive contribution of both daily conditional volatility information and daily stock-return information.

Residual diagnostic tests also supported the adequacy of the final MIDAS specification. The Ljung–Box statistic at lag 10 was 12.771 with a p-value of 0.237. Because the p-value exceeded 0.05, the null hypothesis of no residual autocorrelation was not rejected, indicating that no statistically significant serial dependence remained in the model residuals. The Jarque–Bera statistic was 2.132 with a p-value of 0.344, and the Shapiro–Wilk statistic was 0.9960 with a p-value of 0.276. In both cases, the null hypothesis of residual normality was not rejected at the 5% level. The agreement between the two normality tests provides additional evidence that the distribution of the final model residuals was compatible with the normality assumption.

Taken together, the empirical findings indicate that daily macro-financial information contained meaningful predictive content for weekly TSE Total Index returns. Changes in the exchange rate were positively associated with weekly stock returns, whereas changes in the global gold price were negatively associated with returns. Conditional volatility in both the foreign-exchange and gold markets contributed additional predictive information, and the inclusion of daily TSE Total Index returns generated a further reduction in out-of-sample forecast errors. Although in-sample indicators such as R^2 , AIC, BIC, and log likelihood also improved across the progressively enriched specifications, the principal evidence was provided by the lower out-of-sample RMSE and MAE values and the statistically significant Diebold–Mariano comparisons. Overall, the findings demonstrate the usefulness of the MIDAS framework for exploiting information contained in higher-frequency daily data when forecasting weekly returns in the Iranian capital market.

4. Discussion and Conclusion

The present study examined the out-of-sample forecasting performance of weekly Tehran Stock Exchange (TSE) Total Index returns using a mixed-frequency MIDAS framework that incorporated daily macro-financial variables, GARCH-based conditional volatility measures, and daily TSE Total Index returns. The results showed that daily changes in the exchange rate were positively associated with weekly stock returns, whereas changes in the global gold price were negatively associated with weekly returns. The oil-price coefficient was positive but did not consistently reach the conventional 5% significance threshold. The inclusion of exchange-rate and gold-price volatility significantly improved the explanatory and forecasting performance of the model, while adding daily TSE Total Index returns produced a further reduction in out-of-sample forecast errors. These findings demonstrate that high-frequency information contains useful predictive content for lower-frequency stock market returns and that the MIDAS framework can preserve information that might otherwise be lost through conventional temporal aggregation.

One of the most important empirical findings was the positive and statistically significant relationship between changes in the exchange rate and weekly TSE Total Index returns. This result suggests that exchange-rate movements contain economically meaningful information for the Iranian equity market. The relationship may be explained through several channels. Exchange-rate depreciation can increase the domestic-currency value of export revenues, improve the nominal earnings outlook of export-oriented firms, raise replacement costs and nominal asset values, and intensify inflation expectations, all of which may affect stock prices. At the same time, the relationship should be interpreted as an empirical association rather than as proof of a direct causal effect. The

finding is consistent with evidence showing that exchange-rate conditions play an important role in the behavior of the Tehran stock market, particularly when interactions among exchange rates, oil prices, gold prices, and market regimes are considered [16]. It is also compatible with broader evidence that macroeconomic variables are significant determinants of stock market performance in emerging and developing markets [17]. Moreover, the presence of nonlinear relationships between economic indicators and capital market behavior reported in other settings supports the idea that exchange-rate effects need not be constant across market states or time periods [18].

The negative coefficient obtained for changes in the global gold price was another notable result. This pattern is consistent with the interpretation of gold as an alternative investment asset. When gold becomes more attractive, investors may reallocate part of their portfolios away from equities, particularly during periods of heightened uncertainty. In such circumstances, a negative association between gold-price movements and stock returns can emerge. The evidence from this study is broadly consistent with the documented role of gold as an important cross-market variable in the Tehran Stock Exchange [16]. The result also supports the broader proposition that financial markets should not be analyzed in isolation because investors react simultaneously to signals from equity, commodity, foreign-exchange, and alternative-asset markets. The importance of cross-market interactions is also evident in recent Iranian evidence showing that cryptocurrency returns may influence the behavior of the TSE Total Index [32]. Taken together, these studies indicate that the TSE operates within a wider portfolio-allocation environment in which movements in alternative assets can carry information about investor sentiment, risk preferences, and expected returns.

The global oil-price variable was positive in the estimated MIDAS models, but its statistical significance was weaker than that of the exchange rate and gold price. This finding suggests that oil-price information may have some relevance for stock return prediction, although its direct incremental effect was less stable in the present sample. One plausible explanation is that oil-price changes affect the Iranian capital market through several competing channels, including export revenues, fiscal expectations, production costs, inflation, and industry-specific profitability. As a result, the aggregate effect on the total stock index may be attenuated when positive and negative sectoral effects offset one another. The weak but positive oil-price relationship is nevertheless consistent with research showing that energy-market returns display complex and frequency-dependent dynamics [19]. It is also in line with evidence that crude-oil price processes are characterized by time-varying volatility and require dynamic modeling rather than simple static assumptions [20]. Therefore, the relatively weaker oil-price coefficient in this study does not imply that oil is irrelevant; rather, it may indicate that its influence is more indirect, nonlinear, sector-specific, or regime dependent.

A further central finding was that exchange-rate and gold-price volatility significantly improved the MIDAS model when these variables were extracted using GARCH(1,1) specifications and added to the forecasting equation. Both volatility coefficients were positive and statistically significant. This finding indicates that the intensity of uncertainty in these markets contained predictive information beyond the directional movement of prices themselves. Such a result is theoretically plausible because investors respond not only to expected changes in macro-financial variables but also to the uncertainty surrounding those changes. Greater exchange-rate volatility, for example, can alter discount rates, risk premia, and expectations regarding corporate profitability. Similarly, fluctuations in gold-market volatility can reflect changing global uncertainty and portfolio rebalancing behavior.

The usefulness of GARCH-based volatility measures is strongly supported by the descriptive and diagnostic results of this study. Significant ARCH effects were observed in both the exchange-rate and gold-price return series, and the estimated GARCH parameters indicated strong volatility persistence. This pattern is consistent with the

established literature on volatility clustering in financial time series and with the continued relevance of GARCH-family models for financial risk measurement [21, 22]. The results also align with the broader quantitative risk-management literature, which emphasizes the importance of modeling changing conditional distributions rather than assuming constant variance [23]. In the Iranian context, previous research has shown that institutional arrangements and market rules can influence daily stock-market volatility, further confirming that volatility is a dynamic component of market behavior rather than a fixed characteristic [24]. The present findings extend this argument by showing that volatility estimated from related markets can also improve forecasts of weekly stock returns.

The statistical significance of both exchange-rate and gold-price volatility further suggests that uncertainty itself acts as an informative state variable. This finding is especially relevant for the Iranian market, where political, macroeconomic, and international developments can generate abrupt shifts in investor expectations. Evidence that political uncertainty affects stock-market volatility in Iran is consistent with this interpretation [30]. Likewise, studies of market reactions to risk-factor disclosures show that investors respond to new information concerning uncertainty and risk exposure [31]. These prior findings support the present result that volatility measures can contribute independently to return forecasting because they summarize the changing risk environment in which investors make decisions.

The strongest forecasting performance was obtained when daily TSE Total Index returns were added to the MIDAS framework. The daily return coefficient was positive and highly significant, and the inclusion of this variable further reduced both RMSE and MAE. This result indicates that recent daily market movements contain incremental information that is not fully captured by macro-financial variables and their volatility measures. High-frequency stock returns may reflect short-term momentum, reversal, liquidity conditions, investor sentiment, and rapid information incorporation. Consequently, aggregating the stock market directly to the weekly frequency may discard information that remains useful for weekly forecasting.

The usefulness of daily market information is consistent with evidence that short-horizon stock-return predictability can persist even when market efficiency is considered [5]. Research showing that weekly options indicators can improve short-term stock-return forecasts also supports the broader argument that high-frequency market variables may contain incremental predictive information [25]. In the Tehran Stock Exchange, day-related market characteristics have also been associated with stock-market performance, suggesting that temporal patterns at the daily level can matter for longer-horizon outcomes [26]. The present study therefore extends this literature by showing that daily stock returns are not only descriptively informative but also contribute to a mixed-frequency forecasting model of weekly returns.

The progressive improvement observed across the MIDAS specifications is one of the clearest empirical contributions of the study. The baseline MIDAS model produced an RMSE of 2.41 and an MAE of 1.76. Adding GARCH-derived volatility reduced these values to 2.18 and 1.59, respectively, while the specification incorporating daily index returns achieved an RMSE of 2.06 and an MAE of 1.47. The same pattern was observed for MAPE, although this measure was treated cautiously because percentage errors can become unstable when actual returns are close to zero. These results indicate that the model benefited from the gradual enrichment of its high-frequency information set.

This improvement supports the methodological logic of mixed-frequency modeling. A central advantage of MIDAS is that it allows a lower-frequency target to be predicted directly from higher-frequency predictors without forcing all series into a common temporal frequency. Previous work has emphasized the value of mixed-frequency

models in nowcasting and forecasting when high-frequency information contains signals that would otherwise be averaged away [13]. Similarly, evidence from risk forecasting suggests that mixed-frequency variables can improve prediction when heterogeneous data sources capture different dimensions of market behavior [14]. A comparative Iranian study also reported that nonlinear MIDAS models can perform favorably relative to conventional ARIMA approaches in forecasting the Tehran stock market [15]. The present results are therefore aligned with both international and domestic evidence regarding the value of preserving mixed-frequency information.

The findings also contribute to the broader literature on financial forecasting methodologies. Recent systematic reviews show that forecasting research increasingly combines statistical, machine-learning, and hybrid approaches because financial markets exhibit nonlinearities, regime changes, and complex temporal dependence [4]. In Iran, deep-learning methods have been used to identify regime changes in the TSE [8], hybrid neural networks have been applied to multiscale index forecasting [10], and NARX neural networks have been used for nonlinear prediction of the TSE Total Index [11]. Other studies have reviewed deep-learning approaches for financial forecasting more generally [7], while feature-extraction research has emphasized the importance of identifying informative signals from noisy stock-market data [27]. The present study complements these approaches rather than directly competing with them. Its contribution lies in combining interpretability, parsimony, and mixed-frequency information within an econometric structure that allows the economic role of specific predictors to remain visible.

The superiority of the richer MIDAS specifications was also confirmed statistically by the Diebold–Mariano tests. The difference between the baseline MIDAS model and the volatility-augmented model was significant, as was the difference between the volatility model and the specification containing daily index returns. This result is important because improvements in RMSE and MAE alone could arise by chance in a particular forecast sample. The formal predictive-accuracy tests indicate that the observed gains were statistically distinguishable rather than merely numerical. This emphasis on out-of-sample evidence is consistent with current forecasting research, which increasingly recognizes that strong in-sample fit does not necessarily imply useful forecasting performance [6, 33]. The present study therefore provides stronger evidence for the usefulness of high-frequency information than would be obtained from R^2 , AIC, or BIC alone.

The diagnostic findings further support the adequacy of the final specification. The Ljung–Box test did not detect significant residual autocorrelation, suggesting that the model captured the main serial dependence in the data. The Jarque–Bera and Shapiro–Wilk tests also failed to reject residual normality at the 5% level. Together with the favorable out-of-sample performance, these results indicate that the final MIDAS specification was statistically well behaved within the study sample. From a broader perspective, the results reinforce the idea that return forecasting should combine multiple dimensions of information, including macroeconomic conditions, uncertainty, and high-frequency endogenous market dynamics. This is also consistent with research emphasizing multiscale investment horizons [29] and advanced portfolio recommendation systems that depend on extracting useful information from complex financial data [28].

The study has several limitations that should be considered when interpreting the findings. First, the analysis focused on the TSE Total Index and therefore did not distinguish between industries, firm sizes, or company-specific exposures to exchange rates, oil prices, and other macro-financial variables. Second, the study period, although sufficiently long for time-series estimation, may still contain structural breaks associated with regulatory changes, sanctions, extraordinary macroeconomic conditions, or changes in market microstructure. Third, the MIDAS models were estimated using a fixed 22-trading-day lag horizon and a Beta weighting function; alternative

lag lengths or weighting structures may generate different results. Fourth, conditional volatility was extracted using the standard GARCH(1,1) specification, which does not explicitly model asymmetric volatility responses or leverage effects. Fifth, the analysis relied primarily on a limited set of daily macro-financial variables and did not include variables such as interest rates, inflation expectations, market liquidity, trading volume, cryptocurrencies, geopolitical uncertainty indices, or investor sentiment. Finally, although the recursive out-of-sample evaluation improves the credibility of the forecasting results, performance may still vary under different forecast windows, crisis periods, or alternative loss functions.

Future research could extend the present framework in several directions. Researchers may compare Beta-weighted MIDAS models with unrestricted MIDAS, exponential Almon weighting, quantile MIDAS, Bayesian MIDAS, Markov-switching MIDAS, or machine-learning-based mixed-frequency approaches. Sectoral or industry-level analyses could determine whether the predictive effects of exchange rates, gold, and oil differ across export-oriented, import-dependent, financial, petrochemical, and manufacturing firms. Future studies could also estimate asymmetric GARCH, EGARCH, GJR-GARCH, or stochastic-volatility models before incorporating volatility into the mixed-frequency framework. Additional high-frequency predictors, including trading volume, market liquidity, investor sentiment, cryptocurrency returns, global equity indices, implied volatility, policy uncertainty, and monetary variables, could also be evaluated. Another promising direction would be to assess forecasting stability across bull, bear, crisis, and normal market regimes and to use rolling-window robustness checks with different estimation and forecast horizons. Finally, combining interpretable MIDAS structures with neural networks or ensemble-learning methods could help determine whether mixed-frequency econometric models and modern machine-learning techniques provide complementary forecasting gains.

The findings have several practical implications for investors, portfolio managers, financial analysts, and market institutions. Weekly forecasting systems for the Tehran stock market should avoid relying exclusively on weekly data and should incorporate daily information whenever reliable observations are available. Exchange-rate developments should be monitored closely because they appear to contain substantial predictive information for weekly stock-market returns. Gold-market conditions should also be incorporated into investment analysis because changes in gold prices may signal portfolio substitution or shifts in risk perception. Risk-management systems can benefit from including time-varying volatility measures rather than using only price changes, particularly when exchange-rate and gold-market uncertainty rises sharply. Portfolio managers may also improve tactical allocation by combining recent daily TSE returns with macro-financial indicators in a unified forecasting framework. For market analysts and institutions, mixed-frequency models offer a practical way to update weekly forecasts continuously as new daily information becomes available, thereby improving responsiveness to changing market conditions and supporting more timely investment and risk-management decisions.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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