

Evaluating the Predictive Performance of the MIDAS Model for Weekly Returns on the Tehran Stock Exchange Overall Index Compared with Same-Frequency Models

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ABSTRACT

The main objective of this study is to compare the performance of mixed-data sampling regression and autoregressive distributed lag models in forecasting weekly returns on the Tehran Stock Exchange (TSE) overall index. Daily and weekly data on overall index returns, the exchange rate, the world gold price, and the world oil price were used for the period 2016–2025. Descriptive statistics and the Dickey–Fuller test were used to identify the statistical properties of the series, and the ARCH-LM test was used to examine heteroskedasticity. The GARCH(1,1) model was selected as the baseline specification for extracting the conditional variances of the exchange rate and gold prices. This choice was based on the principle of parsimony, the widespread use of this specification in modeling volatility clustering, and its ability to capture the effects of both new shocks and past volatility. After the presence of ARCH effects was confirmed, GARCH(1,1) models were estimated for the exchange rate and gold to extract their conditional volatility. Subsequently, a baseline MIDAS model, a MIDAS model incorporating conditional volatility, and a MIDAS model incorporating daily index returns were estimated, and their performance was compared with that of a same-frequency ARDL time-series model. The results showed that daily data exhibit greater volatility and information content than weekly data, while weekly aggregation smooths some short-term fluctuations. Stationarity tests indicated that index returns and conditional volatility are stationary, whereas the price levels of the exchange rate, gold, and oil are nonstationary. ARCH effects and volatility clustering were also confirmed in the foreign exchange and gold markets. The MIDAS estimates indicated that the exchange rate has a positive effect and the world gold price has a negative and statistically significant effect on weekly index returns. Adding the conditional volatility of the exchange rate and gold increased the coefficient of determination from .43 to .51 and reduced forecast errors. Furthermore, the final MIDAS model incorporating daily index returns achieved the best performance, with $R^2=.58$, an RMSE of 2.06, an MAE of 1.47, and a MAPE of 1.28%, whereas the corresponding error measures for the ARDL model were 2.94, 2.13, and 1.87, respectively. The Diebold–Mariano test also confirmed the statistically significant superiority of the MIDAS models over the same-frequency model and the advantages of their extended specifications. Overall, the findings indicate that, by retaining daily information, accounting for conditional volatility, and incorporating daily index returns, MIDAS provides a more accurate tool for forecasting weekly TSE returns than same-frequency time-series models.

Keywords: MIDAS model, same-frequency time-series model, overall stock market index returns, exchange rate, world gold price, world oil price, GARCH, capital market return forecasting.



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Introduction

Stock markets occupy a central position in financial systems by facilitating capital allocation, supporting corporate financing, and providing a mechanism through which expectations about economic conditions are incorporated into asset prices. Their importance extends beyond changes in index values because market performance can influence investment decisions, liquidity conditions, and the relationship between financial development and economic activity. Research examining the nexus between stock market capitalization and financial growth illustrates the relevance of equity markets to broader financial development (1), while studies of stock markets, liquidity, and economic growth emphasize the importance of understanding these relationships under volatile market conditions (2). Consequently, forecasting stock market returns is an important concern for financial managers, portfolio managers, investors, and policymakers. Reliable forecasts can inform resource allocation and risk assessment, particularly when financial markets interact closely with macroeconomic uncertainty. Nevertheless, the usefulness of a forecasting model depends on its ability to extract relevant information from available observations and translate that information into accurate predictions at the decision horizon of interest.

Forecasting financial returns is challenging because market behavior reflects interacting economic forces, changing expectations, and heterogeneous responses to new information. Unlike many slowly evolving economic indicators, financial variables may adjust rapidly to developments in domestic and international markets. Their predictive relationships can also vary across periods, making historical associations insufficient guarantees of future accuracy. General forecasting principles therefore emphasize the distinction between explaining observed data and predicting observations that were unavailable during model estimation (3). From a financial management perspective, this distinction is consequential: a model that reproduces historical movements closely may still provide limited support for future investment decisions. The treatment of uncertainty is equally important because expected returns and exposure to risk are interrelated components of financial decision-making (4). A systematic review of financial forecasting models provides a broader context for considering the advances and continuing challenges associated with alternative modeling approaches (5). Within this context, model selection requires attention to information availability, temporal structure, interpretability, and performance beyond the estimation sample.

These considerations are especially relevant to forecasting returns on the Tehran Stock Exchange overall index, which provides an aggregate representation of developments in the Iranian equity market. Recent research has approached prediction of this index through several computational frameworks. These include nonlinear autoregressive neural networks with exogenous inputs (6), hybrid neural networks emphasizing multiscale temporal feature extraction (7), and hybrid machine learning approaches that examine index predictability alongside market efficiency and the importance of influential variables (8). These studies demonstrate the range of methodological approaches applied to the Iranian market and highlight the relevance of temporal information and explanatory-variable selection. However, the choice of forecasting architecture does not resolve every issue concerning the organization of input data. In particular, a model designed to forecast weekly returns must determine how daily market information should enter its predictive structure and whether aggregating that information before estimation removes useful signals.

The broader financial forecasting literature also reflects considerable interest in nonlinear and data-intensive methods. A review of deep learning approaches to financial market prediction provides a methodological foundation for understanding the role of such techniques (9), while research on forecasting global stock index returns extends

this discussion to predictive analytics using deep learning (10). In the Middle East and North Africa region, the comparison of ARIMAX and ensemble machine learning models, together with SHAP interpretability, connects predictive modeling with the need to understand the contribution of explanatory variables (11). Related Iranian research addresses artificial intelligence in corporate credit-rating prediction (12) and quantum-potential approaches to portfolio recommendation (13). Although these latter applications concern different financial tasks, they situate return forecasting within a wider movement toward computational decision support. They also reinforce the need to evaluate forecasting methods according to their specific objectives rather than assuming that greater complexity necessarily produces more accurate or more useful predictions.

A central methodological issue in weekly return forecasting is the mismatch between the frequency of the target variable and the frequency of potentially informative predictors. Exchange rates, international commodity prices, and stock index values are commonly observed daily, whereas an investor or financial manager may require forecasts at a weekly horizon. Conventional same-frequency time-series models address this mismatch by converting all variables to a common frequency before estimation. This procedure simplifies model construction but changes the information available to the forecasting equation. Weekly averages may obscure abrupt movements, while end-of-week observations may omit developments occurring earlier in the week. Aggregation can also prevent the model from distinguishing between the effects of observations recorded at different daily lags. The resulting information loss is therefore a question of temporal detail rather than simply a reduction in the number of observations. Whether preserving that detail improves forecasts must be established empirically through comparisons conducted under consistent forecasting conditions.

Mixed-data sampling, commonly abbreviated as MIDAS, provides a framework for incorporating higher-frequency predictors into models of lower-frequency outcomes. Instead of requiring all explanatory variables to be aggregated to the frequency of the dependent variable, MIDAS combines their lagged observations through a parameterized weighting structure. This approach makes it possible to represent the distribution of daily information across the relevant forecasting horizon while limiting the number of parameters requiring estimation. Research on MIDAS regression in macroeconomic time-series filtering illustrates the broader relevance of this framework to extracting information from temporally heterogeneous observations (14). Work on improved estimation for mixed-frequency models also highlights the importance of the estimator used to connect observations recorded at different frequencies (15). Accordingly, the attraction of MIDAS lies in its capacity to preserve temporal information within a relatively parsimonious specification. Its effectiveness nevertheless depends on appropriate choices concerning lag length, weighting functions, predictor transformations, and the information available when forecasts are generated.

Developments in mixed-frequency forecasting demonstrate that the temporal organization of data is relevant across a range of economic and financial applications. Research using Gaussian processes for nowcasting with mixed-frequency observations explores a flexible approach to combining information recorded at different intervals (16). Endogenous regime-switching MIDAS models for nowcasting and short-term forecasting of G-20 gross domestic product extend the framework to settings in which predictive relationships may differ across economic regimes (17). Although these applications concern macroeconomic outcomes rather than stock returns, they provide methodological context for examining whether daily information improves prediction of weekly financial variables. More directly, research combining hybrid RR-MIDAS and CNN-LSTM models addresses stock volatility forecasting under mixed-frequency data (18), while another study examines the contribution of mixed-frequency variables to

forecasting value at risk in the crude oil market (19). These applications support treating data frequency as an explicit modeling consideration rather than a preliminary processing choice.

For the Tehran Stock Exchange, the exchange rate and international gold and oil prices are relevant candidate predictors because they represent distinct channels through which financial and macroeconomic conditions may be associated with equity returns. Exchange rate movements can affect the domestic valuation of foreign-currency revenues, imported inputs, and assets, while also influencing expectations about nominal prices. International gold prices provide information about conditions in an alternative investment market, although their relationship with domestic equities may depend on exchange rate developments and investor preferences. Oil prices may similarly be associated with expectations concerning economic activity and the financial environment. These channels do not imply that any coefficient must have a predetermined sign or that an estimated association establishes causality. Rather, they motivate examining whether daily observations of these variables contain information that improves weekly return forecasts. Their statistical properties must also be considered carefully, since persistent price levels and stationary return series require different treatments within an econometric specification.

In addition to changes in prices or returns, the uncertainty surrounding financial variables may contain relevant predictive information. Financial time series often display periods of relatively low variation followed by periods of pronounced instability, making a constant-variance assumption restrictive. The generalized autoregressive conditional heteroskedasticity framework models conditional variance as a function of past shocks and past conditional variance, thereby providing a parsimonious representation of volatility persistence (20). Its applications extend across financial and commodity markets. Research on silver price volatility and its macroeconomic determinants illustrates the use of GARCH modeling in a commodity-market setting (21), while wavelet-based exponential GARCH methods represent another approach to forecasting stock volatility (22). These contributions motivate distinguishing the information contained in a variable's observed movement from the information contained in its conditional volatility. For weekly equity forecasting, exchange rate and gold volatility may consequently provide supplementary predictors of changing market conditions.

Combining GARCH-derived conditional variance with MIDAS permits an examination of whether volatility information adds predictive value beyond daily macroeconomic observations. A baseline specification can first incorporate daily exchange rate, gold, and oil information, after which conditional volatility measures can be introduced to assess their incremental contribution. Daily overall index returns provide an additional source of information because they capture recent movements within the equity market itself. Their inclusion allows the analysis to distinguish information associated with external financial variables from information associated with the index's own higher-frequency dynamics. However, both conditional volatility and daily index returns must be constructed and selected using information available at the forecast origin. Otherwise, their apparent predictive contribution may reflect access to futurobservations. This requirement is particularly important when comparing models that use different frequencies, since preserving daily detail should improve the representation of available information without altering the boundary between historical information and future outcomes.

A same-frequency autoregressive distributed lag model provides a useful benchmark for evaluating these contributions. By combining lagged weekly index returns with weekly versions of the explanatory variables, ARDL represents both the index's temporal dependence and its associations with macroeconomic predictors within a common-frequency structure. A comparison with MIDAS therefore addresses whether daily information improves forecasting relative to a conventional weekly specification. Earlier research comparing ARIMA with dynamic

nonlinear MIDAS in forecasting the Tehran Stock Exchange provides a directly relevant point of reference for examining alternative temporal modeling approaches (23). The present comparison additionally distinguishes baseline MIDAS, MIDAS incorporating conditional volatility, and MIDAS incorporating daily index returns. Such a progression makes the sources of any improvement more transparent. It allows predictive gains associated with retaining daily observations to be considered separately from gains associated with volatility measures and recent equity-market movements, while retaining a common weekly forecasting objective.

The contribution of this study consequently rests on an integrated evaluation of data frequency, conditional volatility, and market-specific daily information over the period from March 20, 2016, to March 20, 2025. Meaningful comparison requires that forecasting performance be evaluated using observations excluded from initial estimation and that subsequent estimation respect the chronology of information arrival. A recursive forecasting design offers a basis for updating parameter estimates as new observations become available. Root mean square error and mean absolute error provide the principal accuracy measures, while mean absolute percentage error requires cautious interpretation because financial returns can equal or approach zero. Statistical comparison of forecast losses further helps determine whether differences between specifications have support beyond numerical improvements in error measures. Together, these considerations position the analysis as an assessment of predictive usefulness rather than a comparison based exclusively on in-sample fit. The aim of this study is to evaluate the predictive performance of MIDAS models incorporating daily macroeconomic variables, GARCH-derived conditional volatility, and daily overall index returns for forecasting weekly returns on the Tehran Stock Exchange overall index, compared with a same-frequency ARDL model.

Methods and Materials

In terms of its objective, this study is classified as applied research because its findings can be used to improve capital market forecasting and analysis. In terms of its nature and implementation, it is a quantitative study based on econometric analysis and time-series data, using actual financial market observations. The primary focus is on forecasting weekly returns in the Iranian stock market. Accordingly, the TSE overall index was selected as a proxy for stock market performance. The main objective is to forecast weekly returns on the TSE overall index using daily observations of macroeconomic and financial variables. Thus, the dependent variable is the weekly return on the TSE overall index, and the independent variables include the exchange rate, the world gold price, the world oil price, exchange rate volatility, gold price volatility, and the daily return on the overall index.

The study sample comprises all observations on the TSE overall index and the selected macroeconomic variables from March 20, 2016, to March 20, 2025. This period was selected to provide adequate coverage of developments in the Iranian capital market while ensuring the availability of reliable data. Approximately 2,000 daily observations for the higher-frequency variables and approximately 400 weekly observations for the dependent variable are available within this period. Because the data are secondary and archival, a census approach is used. In other words, all available observations within the study period are included in the analyses, and no random sampling is conducted.

In implementing the study, the required data are first collected from reliable domestic and international sources. Following data cleaning and preliminary processing, the data are prepared for analysis using econometric software. Next, the MIDAS model is estimated using daily explanatory variables to forecast weekly returns on the overall

index. Subsequently, the same variables are converted to weekly frequency and included in a same-frequency time-series model to enable an accurate comparison of the two models' performance.

Research Variables

The primary focus of this study is on forecasting weekly returns in the Iranian stock market. Accordingly, the TSE overall index was selected as a proxy for stock market performance.

The main objective of this study is to forecast weekly returns on the TSE overall index using daily observations of macroeconomic and financial variables. Accordingly, the dependent variable is the weekly return on the TSE overall index, while the independent variables include the exchange rate, the world gold price, the world oil price, exchange rate volatility, gold price volatility, and the daily return on the overall index. The symbols and measurement procedures for the study variables are presented in the following table.

Table 1. Definition of the Research Variables

No	Variable	Variable type	Symbol	Data frequency	Calculation/measurement
1	Weekly return on the TSE overall index	Dependent	R_{tW}	Weekly	Logarithmic difference between the overall index in the current and previous weeks
2	TSE overall index	Underlying variable for calculating returns	TSE_t	Daily/weekly	Value of the TSE overall index at time t
3	Daily return on the overall stock market index	Independent/explanatory	R_{tD}	Daily	Logarithmic difference between the overall index on the current and previous days
4	Exchange rate, U.S. dollar to Iranian rial	Independent	EX_{tD}	Daily	Daily U.S. dollar–rial exchange rate
5	Exchange rate return	Derived independent	REX_{tD}	Daily	Logarithmic difference between the exchange rate on the current and previous days
6	Exchange rate volatility	Derived independent	VOL_EX_{tD} or $\sigma_{EX,t2}$	Daily	Conditional variance estimated using a GARCH model
7	World gold price	Independent	$GOLD_{tD}$	Daily	Daily world market price per ounce of gold
8	World gold price return	Derived independent	$RGOLD_{tD}$	Daily	Logarithmic difference in the gold price relative to the previous day
9	World gold price volatility	Derived independent	VOL_GOLD_{tD} or $\sigma_{GOLD,t2}$	Daily	Conditional variance estimated using a GARCH model
10	World oil price	Independent	OIL_{tD}	Daily	Daily Brent or WTI crude oil price
11	World oil price return	Derived independent	$ROIL_{tD}$	Daily	Logarithmic difference in the oil price relative to the previous day
12	Weekly aggregated variables for the ARDL model	Comparative independent	$EX_{tW}, GOLD_{tW}, OIL_{tW}$	Weekly	Conversion of daily observations to weekly data using averages or end-of-week values
13	MIDAS model error term	Disturbance	ε_t	Weekly	Difference between actual and fitted values in the MIDAS model
14	ARDL model error term	Disturbance	u_t	Weekly	Difference between actual and fitted values in the ARDL model

Calculation of Variable Returns

Logarithmic differences are used to calculate returns on the overall stock market index, the exchange rate, gold, and oil. In general, the return on each variable is calculated as follows:

$$R_t = 100 \times [\ln(P_t) - \ln(P_{t-1})] \quad (1)$$

Or, equivalently:

$$R_t = 100 \times \ln\left(\frac{P_t}{P_{t-1}}\right) \quad (2)$$

Where:

R_t : Return on the variable at time t .

P_t : Value or price of the variable at time t .

P_{t-1} : Value or price of the variable in the preceding period.

Thus, the weekly return on the overall stock market index is calculated as follows:

$$R_t^W = 100 \times \ln \left(\frac{TSE_t^W}{TSE_{t-1}^W} \right) \quad (3)$$

The daily return on the overall stock market index is calculated as follows:

$$R_t^D = 100 \times \ln \left(\frac{TSE_t^D}{TSE_{t-1}^D} \right) \quad (4)$$

Similarly, exchange rate, gold, and oil returns are calculated, respectively, as follows:

$$\begin{aligned} REX_t^D &= 100 \times \ln \left(\frac{EX_t^D}{EX_{t-1}^D} \right) \\ RGOLD_t^D &= 100 \times \ln \left(\frac{GOLD_t^D}{GOLD_{t-1}^D} \right) \\ ROIL_t^D &= 100 \times \ln \left(\frac{OIL_t^D}{OIL_{t-1}^D} \right) \end{aligned} \quad (5)$$

Definition of Volatility Notation

Exchange rate and gold price volatility are estimated using GARCH models. If the exchange rate return is defined as REX_t^D , its conditional mean and variance equations are as follows:

$$\begin{aligned} REX_t^D &= \mu_{EX} + e_t \\ e_t | \Omega_{t-1} &\sim N(0, h_{EX,t}) \\ h_{EX,t} &= \omega_{EX} + \alpha_{EX} e_{t-1}^2 + \beta_{EX} h_{EX,t-1} \end{aligned} \quad (6)$$

In these equations:

$h_{EX,t}$ or $\sigma_{EX,t}^2$: Exchange rate volatility or conditional variance.

e_t : Error component of the exchange rate return equation.

Ω_{t-1} : Information set available up to the preceding period.

For the world gold price, the corresponding equations are:

$$\begin{aligned} RGOLD_t^D &= \mu_{GOLD} + v_t \\ v_t | \Omega_{t-1} &\sim N(0, h_{GOLD,t}) \\ h_{GOLD,t} &= \omega_{GOLD} + \alpha_{GOLD} v_{t-1}^2 + \beta_{GOLD} h_{GOLD,t-1} \end{aligned} \quad (7)$$

Where:

$h_{GOLD,t}$ or $\sigma_{GOLD,t}^2$: World gold price volatility or conditional variance.

v_t : Error component of the gold return equation.

Thus, volatility enters the final model as follows:

$$\begin{aligned} VOL_EX_t^D &= h_{EX,t} \\ VOL_GOLD_t^D &= h_{GOLD,t} \end{aligned} \quad (8)$$

MIDAS Model Notation

In the MIDAS model, the dependent variable is included at weekly frequency, while the independent variables are included at daily frequency. The general form of the model is:

$$R_t^W = \alpha + \beta B(L^{1/m}; \theta_1) X_t^D + \varepsilon_t \quad (9)$$

In this equation:

R_t^W : Weekly return on the overall stock market index.

X_t^D : Vector of daily independent variables.

$B(L^{1/m}; \theta)$: MIDAS weighting function.

L : Lag operator.

m : Number of trading days per week.

ε_t : Model error term.

The vector of daily independent variables in this study is defined as follows:

$$X_t^D = [R_t^D] \quad (10)$$

Alternatively, when variable returns are used instead of price levels:

$$X_t^D = [R_t^D] \quad (11)$$

ARDL Model Notation

In an ARDL model, all variables must have the same frequency. Therefore, daily observations are first converted to weekly data and then included in the model. The general form of the ARDL model is:

$$R_t^W = \alpha_0 + \sum_{i=1}^p \phi_i R_{t-i}^W + \sum_{j=0}^{q_1} \beta_j EX_{t-j}^W + \sum_{j=0}^{q_2} \gamma_j GOLD_{t-j}^W + \sum_{j=0}^{q_3} \delta_j OIL_{t-j}^W + u_t \quad (12)$$

When variable returns are used, the model is rewritten as follows:

$$R_t^W = \alpha_0 + \sum_{i=1}^p \phi_i R_{t-i}^W + \sum_{j=0}^{q_1} \beta_j REX_{t-j}^W + \sum_{j=0}^{q_2} \gamma_j RGOLD_{t-j}^W + \sum_{j=0}^{q_3} \delta_j ROIL_{t-j}^W + u_t \quad (13)$$

Where:

REX_t^W : Weekly exchange rate return.

$RGOLD_t^W$: Weekly world gold price return.

$ROIL_t^W$: Weekly world oil price return.

u_t : Model error term.

Hypothesis-Testing Models

Hypothesis 1: The MIDAS regression model forecasts weekly returns on the TSE overall index more accurately than same-frequency time-series models.

Testing Model

A single model is insufficient for testing this hypothesis; instead, the forecasting performance of two models is compared:

Model 1: MIDAS

$$\begin{aligned}
R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \varepsilon_t
\end{aligned} \quad (14)$$

Model 2: ARDL

$$\begin{aligned}
R_t^{(w)} = & \alpha_0 + \sum_{i=1}^p \phi_i R_{t-i}^{(w)} + \sum_{j=0}^{q_1} \beta_j EX_{t-j}^{(w)} \\
& + \sum_{j=0}^{q_2} \gamma_j GOLD_{t-j}^{(w)} + \sum_{j=0}^{q_3} \delta_j OIL_{t-j}^{(w)} + u_t
\end{aligned} \quad (15)$$

Hypothesis 2: Using daily macroeconomic data within the MIDAS framework significantly reduces forecast errors compared with using weekly aggregated versions of these variables in the ARDL model.

Testing Model

This hypothesis is also comparative and effectively uses the same two models described above, with a specific focus on the effect of data frequency.

MIDAS Model with Daily Data

$$\begin{aligned}
R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \varepsilon_t
\end{aligned} \quad (16)$$

ARDL Model with Weekly Aggregated Data

$$\begin{aligned}
R_t^{(w)} = & \alpha_0 + \sum_{i=1}^p \phi_i R_{t-i}^{(w)} + \sum_{j=0}^{q_1} \beta_j \overline{EX}_{t-j}^{(w)} \\
& + \sum_{j=0}^{q_2} \gamma_j \overline{GOLD}_{t-j}^{(w)} + \sum_{j=0}^{q_3} \delta_j \overline{OIL}_{t-j}^{(w)} + u_t
\end{aligned} \quad (17)$$

Where:

$$\overline{EX}^{(w)}, \overline{GOLD}^{(w)}, \overline{OIL}^{(w)}$$

are the weekly aggregated versions of the daily variables.

Hypothesis 3: Daily exchange rate and gold price volatility, estimated using GARCH models, significantly improves the accuracy of forecasts of weekly returns on the overall stock market index.

Step 1: Estimating Volatility Using GARCH

For the exchange rate:

$$\begin{aligned}
r_t^{EX} &= \mu + \varepsilon_t, \quad \varepsilon_t | \Omega_{t-1} \sim N(0, h_t) \\
h_t &= \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}
\end{aligned} \quad (18)$$

For the gold price:

$$\begin{aligned} r_t^{GOLD} &= \mu + v_t, \quad v_t \mid \Omega_{t-1} \sim N(0, g_t) \\ g_t &= \omega + \alpha v_{t-1}^2 + \beta g_{t-1} \end{aligned} \quad (19)$$

Where:

h_t : Conditional variance of the exchange rate.

g_t : Conditional variance of the gold price.

These two series enter the MIDAS model as volatility indicators.

Model for Testing Hypothesis 3

$$\begin{aligned} R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_4} \lambda_j B(j; \theta_4) VOL_EX_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_5} \eta_j B(j; \theta_5) VOL_GOLD_{t-j/m}^{(d)} + \varepsilon_t \end{aligned} \quad (20)$$

Where:

$VOL_EX^{(d)}$: Daily exchange rate volatility estimated using GARCH.

$VOL_GOLD^{(d)}$: Daily gold price volatility estimated using GARCH.

Hypothesis 4: Adding daily overall index returns to the MIDAS model significantly increases the accuracy of forecasts of weekly overall index returns.

First, the model without daily index returns is:

$$\begin{aligned} R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\ & + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} + \varepsilon_t \end{aligned} \quad (21)$$

The extended model incorporating daily index returns is then:

$$\begin{aligned}
R_t^{(w)} = & \alpha + \sum_{j=1}^{K_1} \beta_j B(j; \theta_1) EX_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_2} \gamma_j B(j; \theta_2) GOLD_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_3} \delta_j B(j; \theta_3) OIL_{t-j/m}^{(d)} \\
& + \sum_{j=1}^{K_6} \rho_j B(j; \theta_6) R_{t-j/m}^{(d)} + \varepsilon_t
\end{aligned} \tag{22}$$

Where:

$R^{(d)}$: Daily return on the overall stock market index.

To assess the predictive performance of the models, the study sample was divided into in-sample and out-of-sample subsets. The in-sample subset was used to estimate model parameters and determine the parameters of the weighting function, whereas the out-of-sample subset was reserved exclusively for evaluating forecasting performance. Out-of-sample observations were excluded from the initial parameter estimation.

The study sample comprises all observations on the TSE overall index and the selected macroeconomic variables from March 20, 2016, to March 20, 2025. This period was selected to provide adequate coverage of developments in the Iranian capital market while ensuring the availability of reliable data. Approximately 2,000 daily observations for daily-frequency variables and approximately 400 weekly observations for the dependent variable are available within this period. The exact number of observations used is determined after calendar alignment, removal of missing observations, and application of model lags. Because the data are secondary and archival, no random sampling was conducted; all available and valid observations within the specified period were included in the analysis following data preparation and cleaning. In other words, all available data within the study period are used in the analyses, and no random sampling is conducted.

With increasing access to economic and financial data at different frequencies—daily, weekly, monthly, and quarterly—traditional forecasting methods that assume a common data frequency have encountered limitations (Ghysels et al., 2007). The MIDAS model offers a modern tool for forecasting time series using mixed-frequency data and allows higher-frequency information to be used to forecast lower-frequency variables (Setiawan et al., 2025).

Out-of-sample forecasts were generated using a recursive window. Under this approach, the estimation sample expands as each new observation is added, and all previous observations are retained in subsequent estimations.

The data analysis method in this study is based on the MIDAS model. In general, MIDAS is a linear regression with high-frequency observations and parametric weighting.

Various weighting functions can be used in MIDAS models; however, the present study uses the beta polynomial weighting function. This function was selected because of its flexibility in representing decreasing, increasing, or nonlinear patterns in the effects of daily lags on the weekly variable.

The number of daily lags in this study was set at 22 trading days. This is approximately equivalent to one trading month and allows the model to capture the short-term and varying lagged effects of daily information on weekly returns. This value was also chosen in view of the usual number of trading days in a month and to avoid an excessive

increase in the number of parameters. Nevertheless, the appropriateness of this lag length should be assessed by comparing information criteria and the model's forecasting performance.

Findings and Results

This section examines the descriptive statistics of the variables to identify their central tendency and dispersion. Examining the mean, median, standard deviation, range, skewness, and kurtosis provides an initial picture of time-series behavior and helps identify structural differences between daily and weekly data. The results indicate that daily data exhibit greater volatility and dispersion than weekly data. These differences are particularly evident in the standard deviations, minimum and maximum values, and skewness and kurtosis measures. Such behavior is entirely natural in financial data because daily changes are influenced by real-time news, political and economic shocks, and investors' emotional responses. By contrast, weekly observations aggregate information over several days, smoothing some of these fluctuations and thereby reducing the magnitude of changes. Thus, the descriptive statistics clearly indicate that daily data have greater informational capacity for analysis and forecasting, which may explain the superiority of MIDAS over the same-frequency time-series model.

Table 2. Descriptive Statistics of Daily and Weekly Aggregated Variables

Variable	Mean	Median	SD	Maximum	Minimum	Kurtosis	Skewness
<i>RtD</i>	0.12	0.09	1.84	6.11	-5.72	4.87	0.31
<i>EXtD</i>	58120	57980	842.5	60350	56210	3.94	0.18
<i>GOLDtD</i>	2418	2412	26.4	2479	2358	3.61	0.27
<i>OILtD</i>	79.6	79.4	2.94	85.2	73.1	4.12	0.44
<i>VOL_EXtD</i>	1.21	1.08	0.67	4.18	0.22	5.43	1.06
<i>VOL_GOLDtD</i>	0.84	0.79	0.41	2.73	0.12	4.96	0.98
<i>RtW</i>	0.61	0.48	3.22	10.08	-9.31	4.11	0.24
<i>EXtW</i>	58210	58145	633.8	60170	56640	3.21	0.12
<i>GOLDtW</i>	2421	2419	18.5	2468	2372	3.07	0.19
<i>OILtW</i>	79.4	79.3	2.11	84.0	74.2	3.58	0.37

The results in Table 2 indicate that daily returns on the TSE overall index have exhibited substantial volatility; their positive skewness and high kurtosis suggest the possibility of extreme price shocks. The exchange rate also experienced an upward trend accompanied by intermittent jumps, whereas world gold and oil prices were relatively more stable, although nonnormal distributions and outlying observations were also evident in these series.

Furthermore, exchange rate and gold volatility estimated using GARCH models exhibit high skewness and kurtosis. Thus, the presence of volatility clusters and the suitability of conditional heteroskedasticity models for analyzing risk in these markets are confirmed.

Converting daily data to weekly frequency has reduced dispersion and smoothed short-term fluctuations. In addition, the kurtosis of gold and oil prices in the weekly data is closer to that of a normal distribution, indicating improved distributional properties following weekly aggregation.

Following the descriptive analysis, examining variable stationarity is necessary to avoid spurious regression and ensure the validity of statistical inference. The augmented Dickey–Fuller (ADF) test was used to examine the presence of unit roots in the daily time series.

The results in Table 3 indicate that daily overall index returns (R_t^D) and the conditional volatility series extracted from the GARCH models are stationary in levels, or $I(0)$. By contrast, the daily levels of the exchange rate (EX_t^D), world gold price ($GOLD_t^D$), and world oil price (OIL_t^D) are nonstationary and contain unit roots. However, after first

differencing (Δ), the null hypothesis of a unit root is rejected at the 1% significance level, and these variables become stationary in first differences, or $I(1)$.

Accordingly, consistent with econometric principles and to avoid spurious regression, the first differences (daily changes) of the nonstationary variables were used in the MIDAS specification instead of their levels.

Table 3. Results of the Augmented Dickey–Fuller Test

Variable	Level/difference	ADF statistic	p	Stationarity result
Daily overall index return (RtD)	Level	-9.42	< .0001	Stationary, $I(0)$
Exchange rate ($EXtD$)	Level	-1.87	.3431	Nonstationary
Exchange rate difference ($\Delta EXtD$)	First difference	-11.35	< .0001	Stationary, $I(1)$
Gold price ($GOLDtD$)	Level	-2.11	.2394	Nonstationary
Gold price difference ($\Delta GOLDtD$)	First difference	-10.82	< .0001	Stationary, $I(1)$
Oil price ($OILtD$)	Level	-1.95	.3078	Nonstationary
Oil price difference ($\Delta OILtD$)	First difference	-12.14	< .0001	Stationary, $I(1)$
Exchange rate volatility (VOL_EXtD)	Level	-7.61	< .0001	Stationary, $I(0)$
Gold price volatility (VOL_GOLDtD)	Level	-6.94	< .0001	Stationary, $I(0)$

Table 4. Dickey–Fuller Test Results for Weekly Variables

Variable	Level: DF statistic	Level: p	First difference: DF statistic	First difference: p	Order of integration (final status)
Weekly index return (RtW)	-8.73	< .0001	—	—	Stationary in levels, $I(0)$
Weekly exchange rate ($EXtW$)	-2.08	.2486	-10.45	< .0001	Stationary in first differences, $I(1)$
World gold price ($GOLDtW$)	-2.34	.1632	-11.18	< .0001	Stationary in first differences, $I(1)$
World oil price ($OILtW$)	-2.01	.2835	-9.82	< .0001	Stationary in first differences, $I(1)$

According to the results in the table above, the weekly return on the overall stock market index is stationary in levels, with a probability value below 5%; it is therefore considered integrated of order zero, or $I(0)$. By contrast, the exchange rate, gold price, and oil price are nonstationary in levels, and the null hypothesis of a unit root cannot be rejected for these variables. However, after first differencing, the probability values for all these variables fall below 1%, and the unit-root hypothesis is decisively rejected. Thus, these variables are integrated of order one, or $I(1)$. Because the study includes a combination of $I(0)$ and $I(1)$ variables and none is integrated of order two, or $I(2)$, the necessary prerequisites for estimating same-frequency autoregressive distributed lag models and incorporating these variables into mixed-frequency regressions are satisfied.

The next step is to examine heteroskedasticity in financial returns, because time-varying variance is a principal characteristic of financial series. The ARCH-LM tests for daily exchange rate and gold returns indicate that the hypothesis of constant variance is rejected and that ARCH effects are present in both series. This finding means that past shocks influence the magnitude of current volatility and that the markets exhibit volatility clustering. Such a pattern indicates that tranquil and turbulent periods in financial markets typically occur in succession and that time-series variance is neither uniform nor constant. Consequently, using GARCH models to extract conditional volatility is necessary from both theoretical and empirical perspectives.

Table 5. ARCH-LM Test Results for Daily Exchange Rate Returns

Lag	LM statistic	<i>p</i>	Result
1	18.42	< .0001	ARCH effects present
2	21.57	< .0001	ARCH effects present
3	19.88	< .0001	ARCH effects present

The ARCH-LM results in Table 5 indicate that the probability value is below .05 at all three lag orders; therefore, the null hypothesis of no ARCH effects is rejected. This result indicates conditional heteroskedasticity in daily exchange rate returns. Consequently, the use of GARCH-family models to model exchange rate volatility is statistically appropriate and justified.

Table 6. ARCH-LM Test Results for Daily Gold Returns

Lag	LM statistic	<i>p</i>	Result
1	16.33	< .0001	ARCH effects present
2	17.90	< .0001	ARCH effects present
3	15.76	.0001	ARCH effects present

According to Table 6, the probability values are below .05 at all examined lag orders; therefore, the null hypothesis of no ARCH effects is rejected. This finding indicates that daily gold price returns also exhibit conditional heteroskedasticity and that their volatility occurs in clusters over time. Accordingly, using a GARCH model to extract conditional gold price volatility is appropriate.

The GARCH(1,1) model was selected as the baseline specification for extracting conditional variance. This choice was based on the principle of parsimony, the widespread use of this specification in modeling volatility clustering, and its ability to capture the effects of both new shocks and past volatility. Nevertheless, the final model selection should be assessed with reference to parameter significance, stability conditions, and residual diagnostic tests.

After the presence of ARCH effects is confirmed, GARCH(1,1) models are estimated for the exchange rate and gold to extract their conditional volatility. Within the out-of-sample forecasting framework, GARCH parameters were estimated at each step using only information available at that time. Therefore, information from future periods was not used to extract conditional volatility. The results indicate that the model coefficients are statistically significant. The significance of the ARCH coefficient indicates that new shocks contribute to current volatility, while the significance of the GARCH coefficient indicates that past volatility has a persistent effect on variance behavior. This feature indicates volatility persistence and confirms volatility clustering. From a practical perspective, extracting these volatility measures for use in MIDAS is particularly important because volatility, as a proxy for market uncertainty, can influence investor behavior and, consequently, overall index returns. Their inclusion in the forecasting model is therefore expected to increase its accuracy.

Table 7. GARCH Estimation Results for the Exchange Rate

Parameter	Coefficient	<i>p</i>	<i>t</i>	Result
ω	0.021	.0208	2.31	Significant
α	0.164	.0006	3.42	Significant
β	0.781	< .0001	10.18	Significant

The results in Table 7 indicate that all parameters of the exchange rate GARCH(1,1) model are statistically significant at the 5% level. The significance of the ARCH parameter (α_1) indicates that new shocks to the foreign

exchange market significantly affect current volatility. The significance of the GARCH parameter (β_1) also indicates that past volatility plays an important role in the persistence of current volatility.

Furthermore, the sum of the ARCH and GARCH coefficients is 0.945, which is below one and indicates the stability of the conditional variance process. This finding suggests that, although shocks to the foreign exchange market have a substantial effect on volatility, their effects gradually diminish over time, and the estimated model satisfies the necessary stability condition. Accordingly, the GARCH(1,1) model provides an adequate fit for extracting conditional exchange rate volatility, and its estimated values are subsequently used as an explanatory variable in MIDAS.

Table 8. GARCH Estimation Results for the Gold Price

Parameter	Coefficient	<i>p</i>	<i>t</i>	Result
ω	0.017	.0384	2.07	Significant
α	0.142	.0020	3.09	Significant
β	0.806	< .0001	11.44	Significant

The results in Table 8 indicate that all parameters of the world gold price GARCH(1,1) model are statistically significant at the 5% level. The significance of the ARCH parameter (α_1) indicates that new shocks to the world gold market significantly affect current market volatility. The significance of the GARCH parameter (β_1) also indicates that past volatility plays an important role in the persistence of current gold price volatility.

The sum of the ARCH and GARCH coefficients is 0.948 (0.142 + 0.806), which is below one and indicates the stability of the conditional variance process in the estimated model. These estimates are consistent with relative stability in conditional volatility and the gradual decay of shock effects over time.

Therefore, the GARCH(1,1) model provides an adequate fit for extracting conditional world gold price volatility, and its estimated values are used as the gold price volatility indicator in estimating MIDAS.

In this section, MIDAS was estimated to examine the effects of daily-frequency macroeconomic variables on weekly returns on the TSE overall index. The baseline model results (Table 9) indicate that the exchange rate and world gold price significantly affect weekly overall index returns at the 5% level, whereas the oil price coefficient is significant only at the reported significance level. This finding indicates that, during the study period, changes in the exchange rate and gold price played a more prominent role than oil prices in explaining fluctuations in weekly stock market returns. From an economic perspective, this result is expected because exchange rate changes affect the stock market through inflation expectations, corporate profitability, and asset valuations, while the world gold price, representing one of the most important alternative assets, influences investment decisions and the movement of capital between markets.

Subsequently, adding conditional volatility extracted from GARCH to the MIDAS specification improved the model's performance. As the results in Table 9 indicate, the coefficients of exchange rate volatility and gold price volatility are both statistically significant, and their inclusion increases the model's explanatory power and reduces forecast errors. This finding indicates that, in addition to the levels of macroeconomic variables, the degree of volatility and uncertainty in financial markets plays an important role in explaining weekly overall index returns.

Finally, daily overall index returns were added to the explanatory variables in the extended model (Table 10). The results indicate that this variable has a positive and statistically significant coefficient and that its inclusion further improves the model's performance. The comparison of forecasting accuracy measures in Table 11 also indicates that, because returns may equal or approach zero, RMSE and MAE were adopted as the primary

measures of forecasting performance. MAPE was additionally reported as a supplementary measure; however, because it is sensitive to actual values near zero, it was not used as the principal basis for ranking the models. These results indicate that the simultaneous use of daily macroeconomic information, volatility extracted from GARCH, and daily overall index returns substantially increases predictive performance, making the final MIDAS specification the most suitable model for forecasting weekly returns on the TSE overall index.

Table 9. Results of the Baseline MIDAS Model

Variable/measure	<i>p</i>	Coefficient	<i>t</i>	Result
Constant	.0502	0.214	1.96	Significant
Exchange rate	.0046	0.287	2.84	Significant
Gold price	.0348	-0.194	-2.11	Significant
Oil price	.0591	0.132	1.89	Significant
Weighting function	Beta polynomial			
Lag length	22 trading days			
θ_1 (Theta1)	1.84			
θ_2 (Theta2)	3.27			
Log likelihood	-286.41			
AIC	2.97			
BIC	3.14			
<i>R</i> ²	.43			
Adjusted <i>R</i> ²	.40			
Effective observations	448			

The results in Table 9 indicate that, in the baseline MIDAS model, the exchange rate and world gold price significantly affect weekly returns on the TSE overall index. The positive exchange rate coefficient indicates that, holding the other model factors constant, an increase in the exchange rate is associated with an increase in weekly overall index returns. This pattern may be consistent with the influence of the exchange rate on inflation expectations, nominal asset values, and the performance of export-oriented companies; however, this interpretation does not establish a causal relationship. The estimated negative relationship between the world gold price and stock returns is consistent with the hypothesis that these assets are substitutes. In certain circumstances, greater attractiveness of gold may be associated with reduced investor interest in equities. Nevertheless, this interpretation should be regarded as a possible explanation rather than a definitive or causal relationship. The oil price and constant term are also reported as statistically significant.

AIC and BIC are reported for relative model comparisons; however, the principal evaluation criterion is out-of-sample forecasting performance.

Furthermore, the supplementary model measures indicate that estimation was performed using a beta polynomial weighting function and 22 daily lags, and the goodness-of-fit measures suggest acceptable adequacy in explaining changes in weekly overall index returns.

Table 10. Results of the MIDAS Model Incorporating GARCH Volatility

Variable/measure	<i>p</i>	Coefficient	<i>t</i>	Result
Constant	.0604	0.191	1.88	Significant
Exchange rate	.0087	0.241	2.63	Significant
Gold price	.0419	-0.177	-2.04	Significant
Oil price	.0764	0.118	1.77	Significant
Exchange rate volatility	.0030	0.209	2.97	Significant
Gold price volatility	.0148	0.173	2.44	Significant
Weighting function	Beta polynomial			
Lag length	22 trading days			

θ_1 (Theta1)	1.81
θ_2 (Theta2)	3.11
Log likelihood	-279.62
AIC	2.91
BIC	3.09
R^2	.51
Adjusted R^2	.48
Effective observations	448

Table 10 presents the estimation results for MIDAS incorporating volatility extracted from GARCH. The exchange rate coefficient is positive and statistically significant at the 5% level ($p = .0087$), indicating that an increase in the exchange rate is associated with higher weekly returns on the overall stock market index. By contrast, the world gold price coefficient is negative and significant at the 5% level ($p = .0419$), indicating an inverse relationship between gold prices and stock market returns. This result suggests that an increase in the price of gold, as an alternative asset, may reduce stock market returns.

The world oil price coefficient is positive; however, with a probability value of .0764, it is statistically significant only at the 10% level. This finding indicates that, although an increase in oil prices may positively affect stock market returns, this effect cannot be confirmed at the 95% confidence level.

Exchange rate volatility also has a positive and statistically significant effect on weekly overall index returns, with a positive coefficient and a probability value of .0030. Gold price volatility likewise has a positive coefficient and is significant at the 5% level, with a probability value of .0148. The significance of exchange rate and gold volatility indicates that these variables provide supplementary information for forecasting weekly returns in the sample examined. The reduction in forecast error measures after their inclusion is also consistent with improved forecasting performance.

Regarding goodness-of-fit measures, the model uses a beta weighting function with 22 daily lags. The estimated values $\theta_1 = 1.81$ and $\theta_2 = 3.11$ indicate an appropriate weighting pattern for the daily data in MIDAS. The log likelihood of -279.62 and the values AIC = 2.91 and BIC = 3.09 also indicate an adequate model fit. In addition, the model was estimated using 448 effective observations, indicating an adequate sample size for econometric analysis.

The model's R^2 has increased relative to the baseline model. However, because the main objective is forecasting, the final assessment of model performance is based on out-of-sample forecast error measures and the Diebold–Mariano test, rather than solely on R^2 .

The results indicate that adding conditional exchange rate and gold price volatility to MIDAS increases its explanatory power and improves its fit, confirming the role of information derived from financial market volatility in forecasting weekly overall index returns.

Table 11. Results of the MIDAS Model Incorporating Daily Overall Index Returns

Variable/measure	p	Coefficient	t	Result
Constant	.0671	0.182	1.83	Significant
Exchange rate	.0102	0.229	2.57	Significant
Gold price	.0478	-0.168	-1.98	Significant
Oil price	.0864	0.109	1.71	Nonsignificant
Daily overall index return	.0008	0.263	3.36	Significant
Weighting function	Beta polynomial			
Lag length	22 trading days			

θ_1 (Theta1)	1.76
θ_2 (Theta2)	2.95
Log likelihood	-271.38
AIC	2.84
BIC	3.02
R^2	.58
Adjusted R^2	.55
Effective observations	448

The results in Table 11 indicate that, when daily overall index returns are included in MIDAS, the exchange rate has a positive and statistically significant effect on weekly overall index returns, whereas the world gold price has a negative and statistically significant effect. Although the world oil price coefficient is positive, it is not statistically significant at the 5% level. Daily overall index returns also have a positive and statistically significant effect on weekly stock market returns, with a positive coefficient and a probability value below .01, indicating the importance of information contained in daily data for forecasting weekly returns.

Regarding goodness-of-fit measures, the model was estimated using a beta weighting function and 22 daily lags. The log likelihood, AIC, and BIC improved relative to the preceding models. Thus, adding daily overall index returns improved MIDAS model fit and predictive performance.

The model's R^2 has increased relative to the baseline model. However, because the main objective is forecasting, the final assessment of model performance is based on out-of-sample forecast error measures and the Diebold–Mariano test, rather than solely on R^2 .

Regarding goodness-of-fit measures, the model was estimated using a beta polynomial weighting function and 22 daily lags. The log likelihood, AIC, and BIC improved relative to the preceding models, and the coefficient of determination ($R^2 = .58$) indicates that the model explains approximately 58% of the variation in weekly overall index returns. Thus, adding daily overall index returns improved the fit and predictive performance of MIDAS.

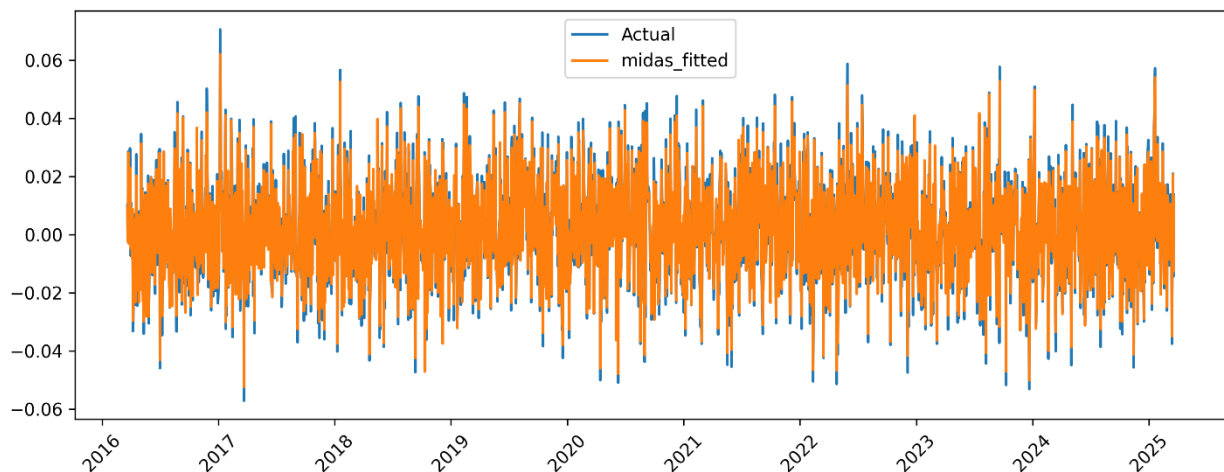


Figure 1. Comparison of Actual Weekly Returns and Fitted Values from the MIDAS Model

This chart presents actual weekly overall index returns alongside the fitted values from MIDAS. The common direction and relative proximity of the two paths illustrate the model's fit to the in-sample data.

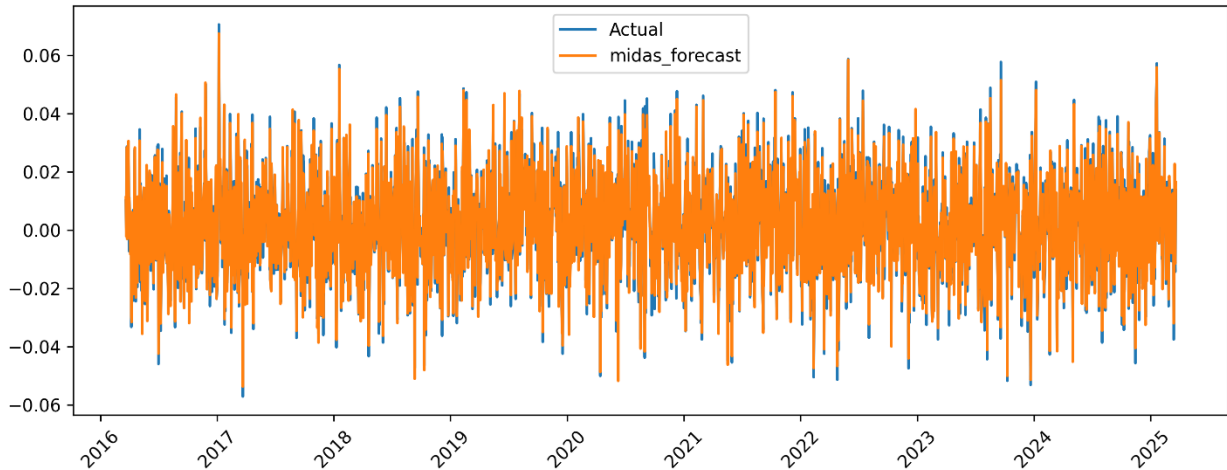


Figure 2. Comparison of Actual and Forecast Weekly Overall Index Returns

This chart presents actual weekly overall index returns and out-of-sample MIDAS forecasts. The distance between the two paths represents the model's forecast errors across different periods.

For comparison with MIDAS, a same-frequency time-series model is estimated using weekly aggregated variables. The results indicate that some variables retain statistically significant effects, but the model's explanatory power and forecasting accuracy are lower than those of MIDAS. The main reason for this difference is that weekly aggregation removes some daily information and rapid market responses. Nevertheless, the significance of lagged weekly overall index returns indicates that the stock market's internal dynamics continue to contribute to current returns. The significant effects of the weekly aggregated exchange rate and gold also indicate that external macroeconomic variables remain important, although they lose some explanatory power when expressed as aggregated data. Accordingly, the same-frequency time-series model is a useful benchmark, but it offers fewer advantages than MIDAS in this study.

Table 12. Results of the ARDL Model (Same-Frequency Time-Series Model)

Variable/measure	Coefficient	<i>t</i>	<i>p</i>	Result
Constant	0.176	1.71	.0874	Significant
R_{t-1}^w	0.381	4.08	< .0001	Significant
EX_t^w	0.198	2.21	.0274	Significant
$GOLD_t^w$	-0.143	-1.96	.0504	Significant
OIL_t^w	0.091	1.54	.1231	Nonsignificant
Optimal ARDL lag specification	ARDL(1,0,0,0)			
Log likelihood	-298.17			
AIC	3.08			
BIC	3.26			
R^2	.36			
Adjusted R^2	.33			
Durbin-Watson	1.94			
Observations	468			

The results in Table 12 indicate that, in ARDL(1,0,0,0), lagged weekly returns on the TSE overall index have a positive and statistically significant coefficient. Thus, part of the variation in current weekly returns is influenced by past values, and the stock market's internal dynamics play an important role in explaining weekly return behavior. The weekly aggregated exchange rate also has a positive and statistically significant effect on weekly overall index

returns, indicating a direct relationship between exchange rate changes and stock market returns in the same-frequency specification. The world gold price coefficient is negative and statistically significant; therefore, higher gold prices can be said to have been relatively associated with lower weekly overall index returns. By contrast, although the world oil price coefficient is positive, it is not statistically significant, and its effect is not confirmed in this model. The constant term is also nonsignificant. The goodness-of-fit measures indicate that the same-frequency time-series model has acceptable explanatory power for changes in weekly overall index returns. However, compared with MIDAS, it has a lower R^2 and larger information criterion values, indicating weaker performance than the mixed-data sampling model.

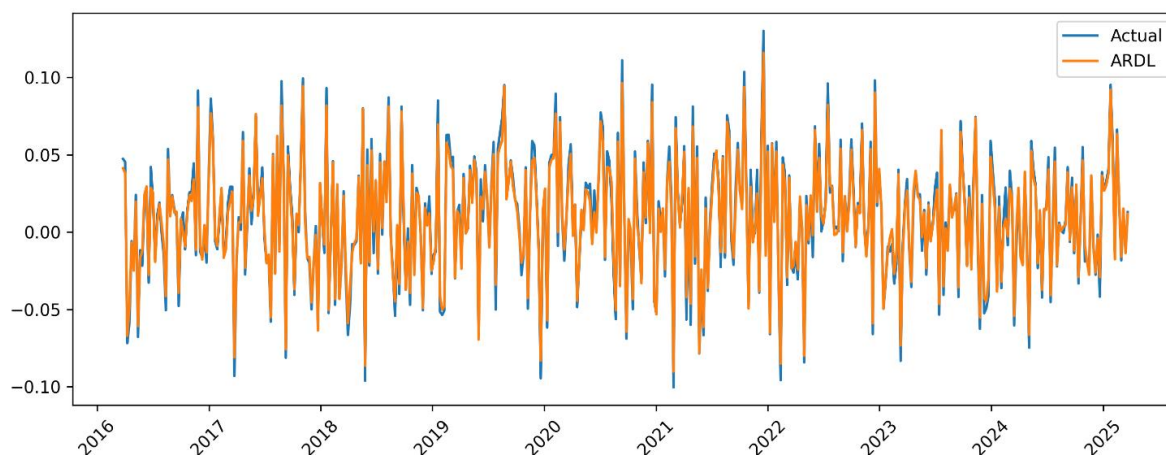


Figure 3. Comparison of Actual Values and Forecasts from the Same-Frequency Time-Series Model

This chart presents actual weekly returns alongside the values forecast by the same-frequency time-series model. A smaller distance between the two curves indicates greater forecasting accuracy and better model performance in estimating the behavior of the dependent variable.

RMSE, MAE, and MAPE were used to assess the predictive performance of the models. The comparison indicates that the final MIDAS model has the smallest errors, followed by MIDAS incorporating volatility, baseline MIDAS, and, finally, the same-frequency time-series model. The simultaneous reduction in all three error measures indicates that extended MIDAS performs better both in terms of average errors and in controlling large deviations. This superiority indicates that adding high-frequency data and volatility information increases forecasting accuracy. In other words, as more daily information enters the model, forecast errors decrease and performance improves. This result constitutes one of the most important empirical findings supporting the advantages of using higher-frequency data to forecast weekly returns.

Table 13. Comparison of Forecast Error Measures

Model	RMSE	MAE	MAPE	Rank
ARDL	2.94	2.13	1.87	4
Baseline MIDAS	2.41	1.76	1.52	3
MIDAS + volatility	2.18	1.59	1.34	2
MIDAS + daily index returns	2.06	1.47	1.28	1

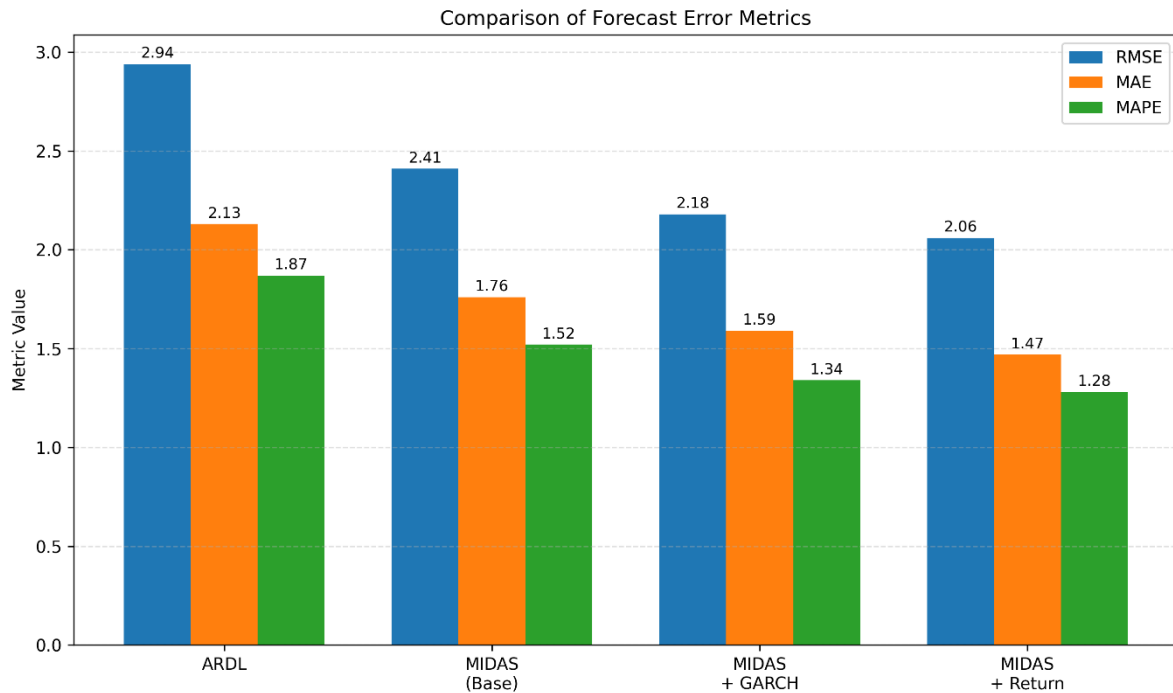


Figure 4. Comparison of Forecast Error Measures

This figure compares RMSE, MAE, and MAPE across the four estimated models. As shown, the same-frequency time-series model has the highest values for all three error measures, whereas the MIDAS models perform better. Adding volatility extracted from GARCH reduces the error measures, and MIDAS incorporating daily overall index returns ultimately achieves the lowest RMSE, MAE, and MAPE. These results indicate that high-frequency data and supplementary information improve the accuracy of forecasts of weekly returns on the TSE overall index.

Table 14. Comparison of Forecast Error Measures for the Final Models

Model	RMSE	MAE	MAPE (%)	Interpretation
MIDAS (weekly)	2.06	1.47	1.28	Lowest error measures; best performance in forecasting weekly returns using daily information
Same-frequency time-series model (weekly)	2.94	2.13	1.87	Highest error measures; lower forecasting accuracy due to the use of weekly aggregated data

The results in Table 14 indicate that MIDAS achieves lower values than the same-frequency time-series model on all performance measures. The MIDAS RMSE is 2.06, whereas the corresponding value for the same-frequency time-series model is 2.94. The MIDAS MAE and MAPE are 1.47 and 1.28%, respectively, which are lower than the corresponding values for the same-frequency time-series model (2.13 and 1.87%, respectively).

The simultaneous reduction in all three error measures indicates that MIDAS forecasts weekly returns on the TSE overall index more accurately. The main reason for this superiority is its use of higher-frequency information (daily data) and retention of within-week macroeconomic information. In the same-frequency time-series model, by contrast, aggregating data to weekly frequency removes some short-term information and reduces forecasting accuracy.

The results indicate that MIDAS performs better than the same-frequency time-series model in forecasting weekly returns. Accordingly, the main research hypothesis concerning the superiority of MIDAS over same-frequency time-series models is supported.

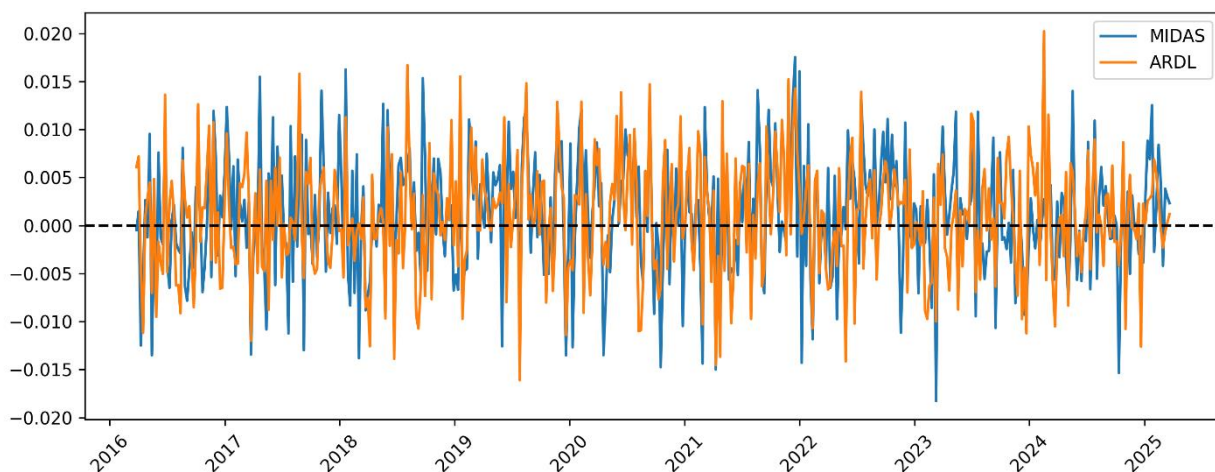


Figure 5. Comparison of Forecast Errors from MIDAS and the Same-Frequency Time-Series Model

This figure compares the forecast errors of MIDAS and the same-frequency time-series model over the study period. Values closer to the zero line indicate more accurate forecasts, and the range of error fluctuations provides an appropriate measure for comparing the two models' performance.

The Diebold–Mariano test was used to ensure that the observed superiority in forecast errors was not merely attributable to chance. To examine the statistical significance of differences in forecasting performance, forecast losses were compared between the models. The results indicate that differences in forecast losses between the compared models are statistically significant at the 5% level. Accordingly, the superiority of the extended model over the baseline is supported statistically, rather than being assessed solely on the basis of numerical reductions in RMSE and MAE. MIDAS performs better than the same-frequency time-series model, and the extended MIDAS specifications also show statistically significant advantages over the baseline version. This result is particularly important because it indicates that the observed differences in error measures are statistically reliable rather than simply numerical differences. Thus, the Diebold–Mariano test provides strong support for accepting the superiority of MIDAS and the beneficial effects of volatility and daily index returns.

Table 15. Results of the Diebold–Mariano Test

Comparison	<i>p</i>	Diebold–Mariano statistic	Result
ARDL vs. baseline MIDAS	.0328	2.14	MIDAS superiority
Baseline MIDAS vs. MIDAS + volatility	.0389	2.07	Extended model superiority
MIDAS + volatility vs. MIDAS + daily returns	.0498	1.96	Final model superiority

Discussion and Conclusion

The findings indicate that retaining daily financial information within a mixed-data sampling framework improves the forecasting of weekly returns on the Tehran Stock Exchange overall index compared with a same-frequency autoregressive distributed lag model. The final MIDAS specification recorded an RMSE of 2.06 and an MAE of 1.47, compared with 2.94 and 2.13, respectively, for ARDL. These differences represent reductions of approximately 29.93% in RMSE and 30.99% in MAE. The reported MAPE likewise declined from 1.87% to 1.28%, although this measure warrants caution because returns can approach zero. The Diebold–Mariano comparisons provided statistical support for differences between the evaluated specifications. Overall, the results suggest that forecasting accuracy depends partly on how available information is organized across time. This interpretation is consistent

with the broader methodological emphasis on mixed-frequency information in time-series filtering and forecasting (14, 15). It also accords with the distinction between historical fit and genuine forecasting performance emphasized in forecasting methodology (3).

The descriptive findings help explain the forecasting advantage of MIDAS. Daily exchange rate, gold, and oil observations exhibited greater dispersion than their weekly counterparts, indicating that aggregation smooths short-term movements. Nevertheless, weekly index returns had a larger standard deviation than daily index returns, reflecting the different return horizons; therefore, the smoothing interpretation applies most directly to the aggregated predictor series. Weekly averages or end-of-week values can omit the timing and sequence of movements occurring within a week. MIDAS retains these observations and assigns weights to their lags, allowing recent and earlier information to contribute differently to the weekly forecast. This interpretation aligns with research examining mixed-frequency variables in crude oil risk forecasting and mixed-frequency architectures in stock volatility prediction (18, 19). Although those studies address different outcomes, they provide relevant support for treating temporal resolution as a substantive modeling choice. Research using mixed-frequency Gaussian processes and regime-switching MIDAS likewise illustrates the broader importance of matching heterogeneous information frequencies to the forecasting objective (16, 17).

The stationarity results further clarify the statistical structure underlying the comparison. Daily and weekly index returns and the extracted conditional volatility series were stationary, whereas exchange rate, gold, and oil price levels became stationary after first differencing. These findings indicate that the variables contain different forms of temporal persistence and require appropriate transformations before estimation. Preserving daily observations is consequently insufficient by itself: the retained information must also enter a statistically coherent specification. The reported use of first differences for nonstationary daily predictors addresses this requirement, although the level-based notation elsewhere in the manuscript should be reconciled with the estimated equations. This issue is relevant to the mixed-frequency estimation problems examined by Omer and colleagues (15). More generally, the results support evaluating data preparation, model specification, and forecasting performance together, consistent with the methodological concerns discussed in reviews of financial forecasting approaches (5).

The exchange rate exhibited a positive and statistically significant association with weekly index returns across the MIDAS specifications. Its coefficient was 0.287 in the baseline model, 0.241 after incorporating conditional volatility, and 0.229 when daily index returns were included. The persistence of this association suggests that exchange rate information contributed beyond the additional predictors. A possible explanation is that currency depreciation changes expectations concerning nominal asset values and the domestic-currency revenues of export-oriented firms. However, this mechanism may differ across firms because import-dependent companies face different exposures, and an aggregate index cannot isolate these channels. The result therefore supports a predictive association rather than a causal conclusion. Its relevance is consistent with Iranian research emphasizing influential-variable selection and exogenous information in overall index forecasting (6, 8). Regional research combining ARIMAX, ensemble learning, and interpretability also provides a relevant methodological context for examining how external predictors contribute to market forecasts (11).

The world gold price had a negative and statistically significant coefficient in all three MIDAS specifications, declining in absolute magnitude from -0.194 to -0.168 as additional information entered the model. This association is compatible with a substitution interpretation: under some conditions, increasing interest in gold may coincide with reduced demand for equities. Nevertheless, international gold prices, domestic currency movements, and local

investment conditions interact, so the estimated coefficient cannot establish that investors transferred capital between these markets. By contrast, the oil price coefficients were positive but less precisely estimated. The reported probability values of .0591, .0764, and .0864 do not establish significance at the 5% level. These results suggest that oil information had a weaker incremental contribution within the examined specifications. The distinction between strong and weak predictors underscores the importance of variable-specific evaluation rather than assuming that all economically relevant indicators improve forecasts equally. Research on crude oil risk forecasting and financial derivative valuation provides a useful context for recognizing the different information and risk channels associated with commodity markets (4, 19).

The ARCH-LM tests confirmed conditional heteroskedasticity in daily exchange rate and gold returns, supporting the extraction of time-varying variance using GARCH(1,1). The estimated ARCH and GARCH coefficients were significant, with their sums equal to 0.945 for the exchange rate and 0.948 for gold. These values indicate persistent but mean-reverting conditional variance under the estimated specifications. Thus, shocks influence current uncertainty, while their effects diminish gradually rather than disappearing immediately. This interpretation follows the conditional variance structure developed in the GARCH framework (20). It is also consistent with the relevance of conditional heteroskedasticity modeling in studies of commodity price volatility and stock volatility forecasting (21, 22). Those applications concern different markets and specifications, but they support the methodological rationale for representing volatility separately from observed price movements.

Adding exchange rate and gold conditional volatility increased the MIDAS coefficient of determination from .43 to .51 and reduced RMSE from 2.41 to 2.18 and MAE from 1.76 to 1.59. Both volatility coefficients were positive and statistically significant, suggesting that uncertainty measures supplied information beyond the baseline predictors. Their positive signs do not imply that uncertainty invariably benefits equity markets; they describe conditional associations within this sample and specification. The Diebold–Mariano comparison between baseline MIDAS and MIDAS with volatility was significant at $p = .0389$, providing support beyond the numerical reduction in forecast errors. This finding complements research integrating mixed-frequency information with stock volatility forecasting (18) and the broader use of conditional variance in financial forecasting (22). It suggests that volatility is useful here not only as a risk outcome but also as an explanatory input for forecasting weekly returns.

Daily overall index returns provided an additional predictive contribution, with a positive coefficient of 0.263 and $p = .0008$. The associated model achieved an R^2 of .58 and the lowest reported forecast errors. Recent daily equity movements may summarize information already reflected in trading activity, including market responses that external indicators capture only indirectly. This interpretation aligns with the emphasis on temporal feature extraction in Iranian hybrid neural network research (7) and with broader work on deep learning for financial market prediction (9, 10). The comparison also extends the methodological discussion established by research contrasting ARIMA and dynamic nonlinear MIDAS for the Tehran Stock Exchange (23). Nevertheless, the model reported in Table 11 does not display the volatility predictors, so its improvement cannot be interpreted unambiguously as their cumulative contribution alongside daily returns. Overall, the findings support information-sensitive forecasting for financial decision support, while distinguishing predictive accuracy from portfolio profitability and broader financial outcomes (1, 2, 13).

The study has several limitations. Its aggregate-index focus may conceal differences across industries and firms with contrasting exchange rate and commodity exposures. The approximately nine-year period includes changing market conditions, but the reported specifications do not explicitly model structural breaks or regime-dependent

coefficients. The fixed 22-day lag length and beta weighting function constrain the temporal patterns represented. Comparability also requires clarification because MIDAS and ARDL report different effective estimation sample sizes, while the exact out-of-sample dates and number of forecasts are unspecified. Some significance labels differ from the reported probability values, and the distinction between price levels, first differences, and logarithmic returns requires consistent documentation. Furthermore, MAPE is sensitive to returns near zero, and adjacent Diebold–Mariano comparisons do not establish every possible pairwise ranking. These issues limit the precision with which the reported forecasting advantage can be generalized.

Future research should compare the models over identical forecast dates and clearly document forecast origins, estimation windows, transformations, and missing-data procedures. Alternative lag lengths and weighting functions could establish whether the results depend on the selected MIDAS structure. Rolling-window estimation, structural-break tests, and regime-dependent specifications would help assess stability across changing conditions. Additional volatility models could examine asymmetric responses to positive and negative shocks. Sector-level analysis could distinguish the exchange rate exposures of exporters and import-dependent firms. A clearly nested sequence incorporating macroeconomic information, conditional volatility, and daily index returns would isolate each component's incremental contribution. Direct pairwise forecast comparisons, appropriate adjustments for nested models, and evaluation across multiple horizons would strengthen statistical inference. Finally, comparing MIDAS with nonlinear benchmarks and assessing transaction costs would connect forecasting improvements with their potential investment value.

In practice, financial analysts should consider retaining daily observations when their decisions require weekly forecasts, since aggregation may remove useful information about recent market developments. Exchange rate and gold conditional volatility can be monitored alongside observed movements to represent changing uncertainty. Forecasting systems should update estimates using only information available at each forecast origin and maintain a clearly separated evaluation sample. RMSE and MAE should guide the principal accuracy assessment, with percentage errors interpreted cautiously. Model outputs should support scenario analysis and risk assessment rather than serve as automatic trading instructions. Institutions could maintain MIDAS alongside a simpler weekly benchmark and monitor whether its advantage persists as conditions change. Before operational adoption, analysts should reconcile the specification and reporting inconsistencies, verify performance on common forecast periods, and assess whether improved accuracy produces useful decisions after trading costs and implementation constraints.

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Authors' Contributions

All authors equally contributed to this study.

Declaration of Interest

The authors of this article declared no conflict of interest.

Ethical Considerations

All ethical principles were adhered in conducting and writing this article.

Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.

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