FORECASTING THE IMPLIED VOLATILITY SURFACE OF EMERGING MARKET CURRENCY OPTIONS: AN EMPIRICAL ANALYSIS

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DECLARATION OF ORIGINALITY

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ABSTRACT

This study aims to evaluate the predictive power of time series and machine learning models, namely Autoregressive (AR), Principal Component Analysis–Vector Autoregression (PCA-VAR), Principal Component Regression (PCR), and Feedforward Neural Networks (FNN), in modeling the implied volatility surfaces of five emerging market currencies (TRY, INR, MXN, ZAR, and BRL against USD). The research assesses model performance using the Root Mean Square Error (RMSE) metric under both the Expanding Window and Rolling Window frameworks. The findings indicate that Principal Component Regression (PCR) and FNN models deliver similarly high precision, particularly for currencies exhibiting lower volatility levels. The study underscores the critical importance of model selection in financial forecasting and suggests that incorporating country-specific macroeconomic or geopolitical factors may further influence model outcomes.

Keywords: Machine learning, Implied Volatility Surface, Forecasting, Currency Options, Emerging Markets

ÖZET

Bu çalışma, beş gelişmekte olan piyasa para biriminin (USD karşısında TRY, INR, MXN, ZAR, BRL) türetilmiş volatilite yüzeylerini modellemede Otoregresif (AR), -Temel Bileşenler Analizi- Çok Değişkenli Otoregresyon (PCA-VAR), Temel Bileşen Regresyonu (PCR) ve İleri Beslemeli Sinir Ağları (FNN) gibi zaman serisi ve makine öğrenimi modellerinin tahmin gücünü incelemeyi amaçlamaktadır. Araştırma, hem Genişleyen Pencere (Expanding Window) hem de Kayan Pencere (Rolling Window) yöntemlerini kullanarak modellerin performansını Kök Ortalama Kare Hata (RMSE) ölçütüne göre değerlendirmektedir. Bulgular, PCR ve FNN modellerinin, özellikle daha düşük volatilite seviyesine sahip para birimlerinde, birbirine yakın ve yüksek doğrulukta sonuçlar verdiğini göstermektedir. Çalışma, finansal tahminde model seçiminin kritik önemde olduğunu vurgulamakta ve ülke bazında makroekonomik ya da jeopolitik faktörlerin model sonuçlarına etki edebileceğini öne sürmektedir.

Anahtar Kelimeler: Makine Öğrenimi, Zımni Volatilite Yüzeyi, Tahminleme, Döviz Opsiyonları, Gelişmekte Olan Piyasalar

TABLE OF CONTENTS

DECLARATION OF ORIGINALITY iii
ABSTRACT iv
ÖZET v
LIST OF TABLES vii
LIST OF FIGURES ix
LIST OF ACRONYMS AND ABBREVIATIONS x
1 INTRODUCTION 1
2 DATA 4
3 METHODOLOGY 6
3.1 Splitting the Data 6
3.2 Autoregressive (AR) 6
3.3 Principal Component Analysis (PCA) 7
3.3.1 Principal Component Regression (PCR) 8
3.3.2 PCA-VAR 8
3.4 FeedForward Neural Network 9
4 FORECAST EVALUATION 15
4.1 Expanding-window Approach 15
4.2 Rolling-window Approach 15
4.3 Forecast Error Measures 16
4.3.1 Forecast Error Measures 16
5 OUT-OF-SAMPLE FORECASTING 17
6 CONCLUSION 20
REFERENCES 22
APPENDICES 24

LIST OF TABLES

Table 6.1: Summary statistics of implied volatility levels across all sample days, maturities, and moneyness levels for each of the five currency options. .. 25

Table 6.2: ADF Test Results 35

Table 6.3: Out-of-Sample One-Day-Ahead RMSE Results for USD/TRY under Expanding-Window Framework 37

Table 6.4: Out-of-Sample One-Day-Ahead RMSE Results for USD/TRY under Rolling-Window Framework 38

Table 6.5: Out-of-Sample One-Day-Ahead RMSE Results for USD/INR under Expanding-Window Framework 39

Table 6.6: Out-of-Sample One-Day-Ahead RMSE Results for USD/INR under Rolling-Window Framework 40

Table 6.7: Out-of-Sample One-Day-Ahead RMSE Results for USD/MXN under Expanding-Window Framework 41

Table 6.8: Out-of-Sample One-Day-Ahead RMSE Results for USD/MXN under Rolling-Window Framework 42

Table 6.9: Out-of-Sample One-Day-Ahead RMSE Results for USD/ZAR under Expanding-Window Framework 43

Table 6.10: Out-of-Sample One-Day-Ahead RMSE Results for USD/ZAR under Rolling-Window Framework 44

Table 6.11: Out-of-Sample One-Day-Ahead RMSE Results for USD/BRL under Expanding-Window Framework 45

Table 6.12: Out-of-Sample One-Day-Ahead RMSE Results for USD/BRL under Rolling-Window Framework 46

Table 6.13: Out-of-Sample Five-Day-Ahead RMSE Results for USD/TRY under Expanding-Window Framework 47

Table 6.14: Out-of-Sample Five-Day-Ahead RMSE Results for USD/TRY under Rolling-Window Framework 48

Table 6.15: Out-of-Sample Five-Day-Ahead RMSE Results for USD/INR under Expanding-Window Framework 49

Table 6.16: Out-of-Sample Five-Day-Ahead RMSE Results for USD/INR under Rolling-Window Framework 50

Table 6.17: Out-of-Sample Five-Day-Ahead RMSE Results for USD/MXN under Expanding-Window Framework 51

Table 6.18: Out-of-Sample Five-Day-Ahead RMSE Results for USD/MXN under Rolling-Window Framework 52

Table 6.19: Out-of-Sample Five-Day-Ahead RMSE Results for USD/ZAR under Expanding-Window Framework 53

Table 6.20: Out-of-Sample Five-Day-Ahead RMSE Results for USD/ZAR under Rolling-Window Framework 54

Table 6.21: Out-of-Sample Five-Day-Ahead RMSE Results for USD/BRL under Expanding-Window Framework 55

Table 6.22: Out-of-Sample Five-Day-Ahead RMSE Results for USD/BRL under Rolling-Window Framework 56

Table 6.23: Out-of-Sample One-Day-Ahead RMSE Performance Using Expanding Window Approach Across Currencies 57

Table 6.24: Out-of-Sample One-Day-Ahead RMSE Performance Using Rolling Window Approach Across Currencies 58

Table 6.25: Out-of-Sample Five-Day-Ahead RMSE Performance Using Expanding Window Approach Across Currencies 59

Table 6.26: Out-of-Sample Five-Day-Ahead RMSE Performance Using Rolling Window Approach Across Currencies 60

LIST OF FIGURES

Figure 1.1: Average Implied Volatility Surfaces from US Dollar/Turkish Lira (USDTRY), US Dollar/Indian Rupee (USDINR), US Dollar/Mexican Peso (USDMXN), US Dollar/South African Rand (USDZAR), and US Dollar/Brazilian Real (USDBRL) for the period 03/06/2013 - 31/05/2023 3

Figure 3.1: Feedforward Neural Network Structure 10

LIST OF ACRONYMS AND ABBREVIATIONS

ADF	Augmented Dickey-Fuller
AR	Autoregressive
ATM	At-the-Money
BIC	Bayesian Information Criterion
BRL	Brazilian Real
DVF	Deterministic Volatility Function
EM	Emerging Market
FNN	Feedforward Neural Network
FX	Foreign Exchange
INR	Indian Rupee
IVS	Implied Volatility Surface
MSE	Mean Squared Error
MXN	Mexican Peso
OLS	Ordinary Least Squares
PACF	Partial Autocorrelation Function
PCA	Principal Component Analysis
PCR	Principal Component Regression
ReLU	Rectified Linear Unit
RMSE	Root Mean Squared Error
SABR	Stochastic Alfa, Beta, Rho

SSE	Sum of Squared Error
TRY	Turkish Lira
USDBRL	US Dollar/Brazilian Real
USDINR	US Dollar/Indian Rupee
USDMXN	US Dollar/Mexican Peso
USDTRY	US Dollar/Turkish Lira
USDZAR	US Dollar/South African Rand
VAR	Vector Autoregressive
ZAR	South African Rand

1. INTRODUCTION

Volatility modeling has long been a prominent topic in the financial literature and continues to evolve alongside the advancement of new methodologies. Market participants rely on these studies and option pricing models to hedge corporate or banking exposures, pursue speculative strategies for alpha generation, and maintain diversified portfolios. Users of these instruments include investors, bankers, fund managers, and corporate professionals, thus creating bilateral demand in the financial markets.

The concept of implied volatility was first introduced through the seminal work of [1], who developed a pricing framework for European options under the assumption that volatility remains constant across strike prices. Although this assumption was initially accepted by practitioners, empirical observations following the 1987 stock market crash revealed that implied volatility varies with moneyness, giving rise to phenomena such as the volatility smile and skew. Consequently, research efforts began to focus on alternative models that better capture these characteristics.

From a theoretical perspective, and indirectly, the concept of non-constant implied volatility was first grounded in the jump-diffusion generalizations introduced by [2] and by [3] within stochastic modeling frameworks. [4] were among the first to propose a mathematical structure for stochastic volatility. A major contribution came from [5], who introduced a closed-form solution for European options using inverse Fourier transforms, significantly advancing tractability in stochastic volatility modeling. [6] extended the Heston model by incorporating jump diffusion to allow for abrupt price changes, thereby improving option pricing performance in equity and derivative markets. For interest rate and Foreign Exchange (FX) options, the Stochastic Alfa, Beta, Rho (SABR) model introduced by [7] became a widely adopted framework. This model features two correlated Brownian motions and assumes that both the underlying asset price and volatility follow stochastic processes.

In the realm of non-stochastic models, the Deterministic Volatility Function (DVF) framework gained prominence with key contributions from [8], [9], and [10]. These models allow implied volatility to vary as a deterministic function of the underlying asset and time. However, DVF models often suffer from overfitting to in-sample data and tend to exhibit poor out-of-sample forecasting performance, as emphasized by [11]. [12], meanwhile, remained faithful to the Black-Scholes structure, introducing numerical adjustments via correction terms derived from the implied volatility surface.

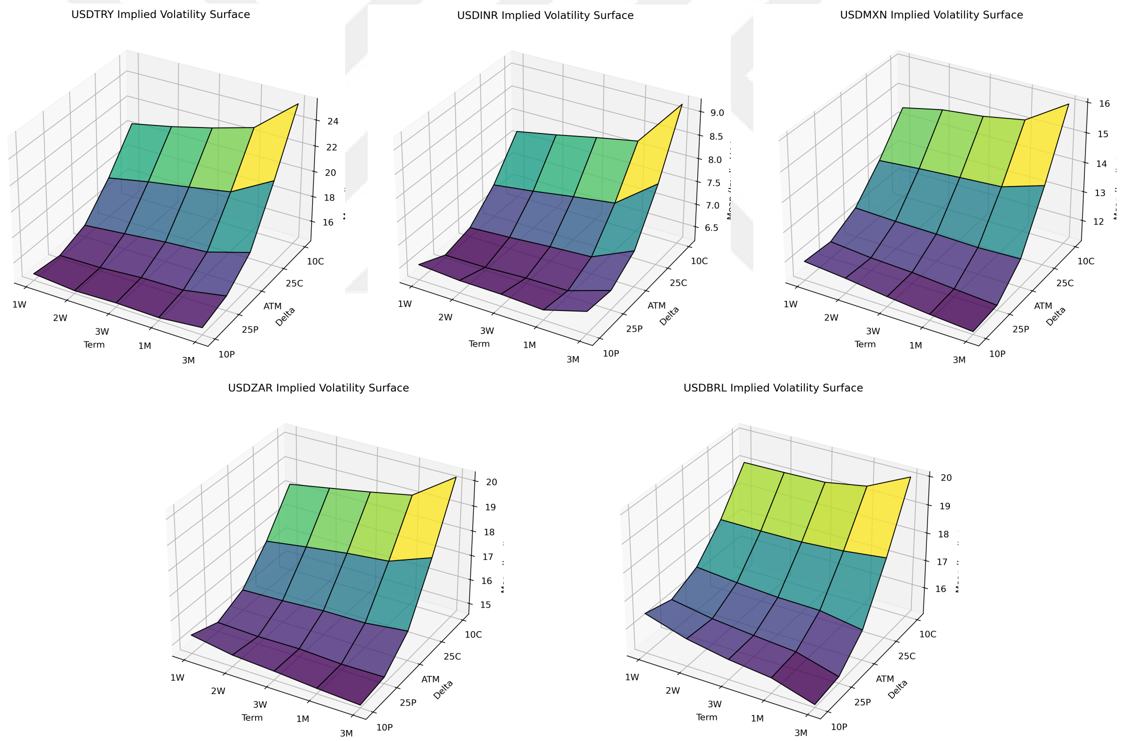
Another stream of research within non-stochastic models has leveraged Principal Component Analysis (PCA), especially in forecasting implied volatility surfaces. In their seminal paper, [13] highlighted the predictive power of PCA in macroeconomic and financial time series. [14] employed PCA alongside Autoregressive (AR) and Vector Autoregressive (VAR) models for both point and interval forecasts, demonstrating that implied volatility indices exhibit predictable dynamics. [15] applied PCA to FX options and successfully combined it with VAR models to produce accurate short-term forecasts. More recently, [16], and [17] integrated PCA with linear and deep learning techniques, contributing to the growing literature on machine learning in financial forecasting.

In this study, our aim is to generate meaningful out-of-sample forecasts of the Implied Volatility Surface (IVS) by integrating principal components with both traditional time-series methods (such as regression and VAR) and machine learning techniques, particularly Feedforward Neural Network (FNN). We evaluated model performance using both expanding-window and rolling-window schemes. Furthermore, we include the *Autoregressive (AR)* model as a benchmark to assess the forecast accuracy of the proposed models.

One of the main contributions of this study is the application of the methodologies developed by [17] to the prediction of the implied volatility surface, thereby extending their framework to a new domain within financial forecasting.

The remainder of this paper is structured as follows. In section 2, describes the data sources, outlines the components of the volatility surface to be predicted, and details the preprocessing steps undertaken to prepare the data for analysis. In section 3, the methodological framework applied to both the data and the forecasting models is introduced. In section 4, presents the forecasting approaches and the performance metrics used to evaluate model accuracy. In section 5, we discuss the in-sample and out-of-sample forecasting results. Finally, in section 6, the study concludes with a summary of the findings and suggestions for future research.

Figure 1.1: *Average Implied Volatility Surfaces from USDTRY, USDINR, USDMXN, USDZAR, and USDBRL for the period 03/06/2013 - 31/05/2023*



2. DATA

The implied volatility data used in this study are sourced from Bloomberg's published Risk Reversal and Butterfly datasets, following the data collection methodologies outlined by [18]. In the extraction process, particular attention was paid to the selection of 10-Delta, 25-Delta, and At-the-Money (ATM) levels to ensure a comprehensive representation of the volatility surface. In addition, the data set encompasses a range of maturities—specifically 1 week, 2 weeks, 3 weeks, 1 month, and 3 months—allowing a detailed examination of the term structure of implied volatility.

The data set comprises daily observations for five major emerging market currencies (Turkish Lira (TRY), Indian Rupee (INR), Mexican Peso (MXN), South African Rand (ZAR), and Brazilian Real (BRL)) quoted against the USD. These particular currencies were chosen because no similarly comprehensive study of Emerging Market (EM) currencies has been conducted to date, and the objective is to enrich the academic literature by focusing specifically on emerging market FX markets. The time span is uniformly maintained across all currency pairs, covering the period from May 31, 2013 to May 31, 2023. This results in a total of 2,609 daily observations per currency, ensuring consistency and robustness in the empirical analysis. Furthermore, the Risk Reversal, Butterfly, and ATM volatilities are separately extracted for both call and put options, providing a more granular view of the implied volatility dynamics in the FX options market.

The risk reversal and butterfly measures are computed as follows:

$$RR_{\Delta} = IV_{\text{Call},\Delta} - IV_{\text{Put},\Delta} \tag{2.1}$$

$$BF_{\Delta} = \frac{IV_{\text{Call},\Delta} + IV_{\text{Put},\Delta}}{2} - IV_{\text{ATM}} \tag{2.2}$$

Volatilities with maturities longer than three months were excluded due to limited market liquidity. Therefore, all forecasts in this study are based on implied volatilities with maturities of up to three months. Initially, missing observations in the data set were handled using interpolation methods to ensure data continuity. Differencing was not applied because the time series was found to be stationary in its original form. Evidence for stationarity is provided by the results of the Augmented Dickey-Fuller (ADF) test, which are reported in Table 2.

3. METHODOLOGY

3.1 Splitting the Data

For each of the five currencies analyzed in this study, the data set contains 2,609 daily observations. During the model training phase, the same train–validation–test data procedure was applied to all models. Before model development, stationarity was verified using the ADF test, and each model was initially trained on the first 1,500 observations, with the subsequent 500 observations reserved for validation. This split was applied only during the training and validation stages; for the forecasting phase, all models again used the same test dataset: observations 2000 through 2,609.

Beyond the train–validation–test partitioning, two additional evaluation strategies were applied to the test data set for all models: the expanding window and rolling window methods. These procedures involved sequential forecast evaluations conducted at 25 observation intervals. For each segment, model performance was measured using the Root Mean Squared Error (RMSE) and the performance scores of each segment were averaged to compute the final out-of-sample RMSE values used for model comparisons.

3.2 Autoregressive (AR)

AR model, denoted as AR(p), constitutes a foundational approach within the Box-Jenkins methodology. It captures the dynamic behavior of a univariate time series by regressing current values to its own past values. The model assumes stationarity and is particularly useful in settings where past observations provide significant explanatory power for future values. Due to its simplicity and interpretability, the AR model is frequently used as a benchmark in time series forecasting studies.

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \varepsilon_t \tag{3.1}$$

The Partial Autocorrelation Function (PACF) plots were examined for each target series. Based on the decay patterns observed in these PACF graphs, the lag orders were computed individually for each of the 25 forecast intervals, and this procedure was applied uniformly across all targets. In all cases, the maximum lag parameter (max lags) was kept constant at 10 when determining the autoregressive lag order.

3.3 Principal Component Analysis (PCA)

PCA, as a nonparametric model, aims to generate new components while preserving the maximum possible variance in the given dataset. These newly derived components are referred to as principal components. Although PCA was introduced into the literature long ago, its application to financial markets was presented by [13] . A similar study was conducted by [19], who employed this method to forecast the implied volatility surface. Furthermore, [14] applied a similar approach in their research on implied volatility prediction. The mathematical derivation of the principal components is based on the computation of eigenvalues and eigenvectors from covariance matrices.

To determine the eigenvalues, the following characteristic equation is used:

$$\det(A - \lambda I) = 0 \tag{3.2}$$

To compute the eigenvectors, the equation:

$$Av = \lambda v \tag{3.3}$$

is solved, which can be rewritten as:

$$(A - \lambda I)v = 0 \tag{3.4}$$

These steps are systematically followed to obtain the eigenvalues and corresponding eigenvectors.

Initially, eigen-decomposition was performed on the training dataset, and the resulting eigenvalues were ranked in descending order. Under the adopted data-splitting scheme, the model - trained in the first 1,500 observations - was then evaluated in the following 500 validation observations, and the number of principal components that minimized RMSE was chosen. This selection procedure was repeated before each forecasting phase at 25 observation intervals, enabling an adaptive determination of the optimal principal component count.

3.3.1 Principal Component Regression (PCR)

Using Principal Component Analysis (PCA), we identified the principal components and subsequently modeled them linearly through Ordinary Least Squares (OLS) regression. By minimizing the squared differences between the predicted values and the actual data points, we derived the estimated linear model.

The fundamental linear regression model is expressed as follows.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \epsilon \tag{3.5}$$

where the Sum of Squared Error (SSE) is given by:

$$SSE = \sum_{i=1}^{n} (Y_i - \hat{Y}_i)^2 \tag{3.6}$$

Using the OLS estimation method, the fitted linear model is obtained as follows:

$$\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 X_1 + \hat{\beta}_2 X_2 + \cdots + \hat{\beta}_n X_n \tag{3.7}$$

To evaluate the performance of the model, we use evaluation metrics such as RMSE, consistent with the evaluation methods used for other models.

3.3.2 PCA-VAR

The Vector Autoregressive (VAR) model is an extension of AR model and serves as a multivariate linear regression model. By incorporating multiple time series variables—where, in our case, these variables are the principal components obtained through

Principal Component Analysis (PCA)—the model leverages the interrelationships among these components to enhance predictive accuracy.

The general formulation of a VAR(n) model for two variables is as follows:

$$\begin{bmatrix} Y_{1,t} \\ Y_{2,t} \\ \vdots \\ Y_{n,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ c_2 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ Y_{2,t-1} \\ \vdots \\ Y_{n,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \vdots \\ \varepsilon_{n,t} \end{bmatrix} \tag{3.8}$$

In this study, a model was constructed based on PCA results under the following constraints: during validation, the maximum lag parameter was kept constant at 10, and the maximum number of principal components to be selected was capped at 5 in order to reduce computational cost. Additionally, the Bayesian Information Criterion (BIC) was employed to identify the optimal lag structure. Consequently, the model parameters were determined in the validation phase by selecting the configurations within these constraints that minimized RMSE.

3.4 FeedForward Neural Network

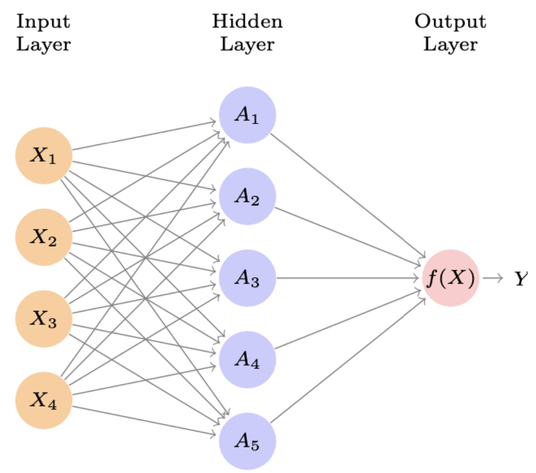
In contrast to other models, the final modeling technique we employ is a non-linear approach, neural network models. Although other methods may also lack transparency in explaining the relationship between inputs and outputs, neural networks stand out as the most complex and highly parameterized models among them, with the lowest level of interpretability.

Despite the existence of various types of neural network, the model utilized in this study is the Feedforward Neural Network (FNN). The fundamental structure of this model consists of an input layer, which contains the independent variables (i.e., the input data), and an output layer, where the final predictions are obtained and model performance is assessed.

A Feedforward Neural Network (FNN) is an artificial neural network characterized by a unidirectional flow of information, with no cycles or feedback connections. Due to its forward-propagating nature, it is referred to as a ”Feedforward” network. During training, the backpropagation algorithm is employed to update the weights, allowing the model to learn from the data provided.

Furthermore, depending on the architecture of the model, hidden layers are also present, which are located between the input and output layers, as exemplified in Figure 2. These layers play a crucial role in enabling non-linear transformations within the model, thereby enhancing its ability to capture complex relationships in the data.

Figure 3.1: *Feedforward Neural Network Structure*



The number of units in the input layer represents the dimensionality of the predictors in the model. Using this framework, we analyzed five different models, referred to as FNN1, FNN2, FNN3, FNN4, and FNN5. In each of these models, the number of nodes in the input layer is 30.

Each node from the input layer is weighted and transformed before being passed to a node in the hidden layer. This weighting process is applied at every transition between layers. The weighted values received by each node in the hidden layer undergo a non-linear transformation through an activation function, which distinguishes the model from linear models.

$$\begin{aligned} f(X) &= \beta_0 + \sum_{k=1}^{K} \beta_k h_k(X) \\ &= \beta_0 + \sum_{K} \beta_k g\left(w_{k0} + \sum_{p} w_{kj} X_j\right). \end{aligned} \tag{3.9}$$

Subsequently, since g(x) serves as an activation function,

$$A_k = h_k(X) = g\left(w_{k0} + \sum_{j=1}^{p} w_{kj} X_j\right). \tag{3.10}$$

For each currency and at every hidden layer, the Rectified Linear Unit (ReLU) activation function is employed. However, as an exception, in the transition from the final hidden layer to the output layer, a linear regression function is applied. This ensures that a single output is generated for each implied volatility value of the target.

$$ReLu(x) = \begin{cases} 0, & \text{if } x < 0 \\ x, & \text{otherwise.} \end{cases} \tag{3.11}$$

In the first of the five models utilized within FNN framework, referred to as FNN1, a hyperparameter space is constructed as part of the cross-validation process. The hyperparameter options explored in this space include the learning rate, neurons per layer, dropout rate, and number of layers. Using these parameters, the model is iteratively trained on the training dataset, testing 30 different combinations of hyperparameters in each iteration.

In the remaining four architectures, the dropout rate (0.2) and the learning rate (0.001) were maintained constant in all designs. However, the models differ in terms of network depth and neurons per layer. During validation, the optimal epoch, in which further training did not produce an improvement in RMSE, was selected using these fixed hyperparameters and then applied in the test phase.

In FNN2 and FNN3, the models incorporate three hidden layers. In FNN2, the neuron configuration per hidden layer is 64, 16, and 4. In FNN3, the configuration is 128, 32, and 8. FNN4 and FNN5 have six and seven hidden layers, respectively. In FNN4, the neuron configuration per hidden layer is 64, 32, 16, 8, 4, and 2. In FNN5, the configuration is 128, 64, 32, 16, 8, 4, and 2. These variations in the number of hidden layers and neuron configurations aim to assess the impact of network depth and complexity on model performance. In designing the model architectures, we followed the geometric pyramid rule, originally suggested by [20] and applied in similar contexts by [17], to determine the number of neurons in each hidden layer, ensuring a pyramidal structure from the first to the last hidden layer. For the FNN1 model, we restricted the first hidden layer to have 128 or 64 neurons. Similarly, in the remaining models, the first hidden layer was initialized with 128 or 64 neurons as a prerequisite.

During the backpropagation process, the computation progresses from the outermost layer to the innermost layer. Throughout this process, the chain rule is applied to propagate the error signal backward. Since the loss function is a composition of the activation function and the network weights, the chain rule is utilized to compute the gradient.

Initially, the partial derivative of the loss function is taken with respect to the activation function in the output layer. In the preceding layers, the derivative is calculated with respect to the weighted input, ensuring that the contribution of each layer to the final error is adequately captured.

$$\frac{\partial L}{\partial a^{(L)}} \tag{3.12}$$

$$\frac{\partial a^{(L)}}{\partial z^{(L)}} \tag{3.13}$$

$$\frac{\partial L}{\partial W} = \frac{\partial L}{\partial a^{(L)}} \cdot \frac{\partial a^{(L)}}{\partial z^{(L)}} \cdot \frac{\partial z^{(L)}}{\partial W} \tag{3.14}$$

In all FNN models, the backpropagation process was carried out using the Adam optimization algorithm, which was introduced by [21]. The derivative calculations previously presented within the framework of the chain rule are employed in the momentum and adaptive scaling steps of the Adam optimizer.

Estimation of the first moment (momentum):

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \tag{3.15}$$

Estimation of the second moment (adaptive scaling of squared gradients):

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \tag{3.16}$$

The weight update step that incorporates adaptive scaling:

$$W_t = W_{t-1} - \frac{\eta \hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{3.17}$$

In the computation of momentum, the momentum coefficient β_1 is set to 0.9, while β_2 is fixed at 0.999.

To prevent overfitting of the model, improve generalization performance, and control the complexity of the model, two regularization techniques were applied: early stopping and dropout.

Early stopping is a widely used regularization method in machine learning, which evaluates prediction accuracy on a validation data set. During each step of the optimization algorithm, the parameter estimates are gradually updated to reduce the prediction errors in the training data set. Throughout this process, if the validation accuracy does not improve for a predefined number of iterations, called the patience parameter, the training process is terminated. The model then identifies the epoch with the lowest validation error within the patience interval as the optimal state, and this epoch is saved. In all neural network models, the initial number of epochs was set to 500, and the patience value was fixed at 50.

Another regularization technique employed in our neural network models is the dropout method (see [22]). This technique is commonly applied to the hidden layers and aims to reduce overfitting while improving the generalization performance of the model. During training, a predefined proportion of neurons are randomly deactivated (i.e., dropped out), meaning that they do not participate in either the forward or backward propagation steps. During the testing phase, all neurons are active again, but their weights are scaled based on the dropout rate used during training.

In the FNN1 model, dropout was treated as a hyperparameter and tuned as part of the hyperparameter search space. In the FNN2, FNN3, FNN4 and FNN5 models, a fixed dropout rate of 0.2 was applied to all hidden layers.

4. FORECAST EVALUATION

4.1 Expanding-window Approach

Expanding-window analyses are commonly used methods in time series modeling. This approach typically works by gradually expanding the training data in fixed increments, keeping the model estimation parameters fixed, and generating predictions for subsequent windows or upcoming data points. This evaluation method is consistent with the one-day-ahead forecasting strategy adopted in the studies by [23]. In addition, the five-day-ahead forecast results are presented in the tabulated section of this study.

In this study, the expanding-window procedure outlined in the section 'Splitting Data' begins by designating the first 1,500 observations as the initial training set and the subsequent 500 observations as the validation set. During the forecasting phase, model parameters are re-estimated every 25 observations, and one-day-ahead forecasts are generated for the following 25 data points using the newly estimated parameters. This window expansion process is repeated 25 times, yielding training sample sizes of 2,000, 2,025, . . . , 2,600, and, in the final iteration, a 2,600-observation training set followed by a nine-observation prediction window, for a total of 2,609 observations. For each of these training partitions, one-day-ahead predictions are produced for the subsequent 25 observations (or nine observations in the last step).

This expanding-window framework and periodic parameter re-estimation are applied consistently across all models evaluated in the analysis.

4.2 Rolling-window Approach

The rolling window approach is used as an alternative model evaluation technique. It is particularly useful when there is evidence of structural instability in the data or when the goal is to reduce the influence of older observations while assigning greater importance to more recent data. This method has been similarly applied by [16], where it supports the modeling framework. In our study, the rolling-window technique was applied to both one-day-ahead and five-day-ahead forecasting models. A fixed window of 1,500 observations was used for training, and at each iteration, the start and end points of the window were advanced by 25 observations. Following each shift, model parameters were re-estimated and held constant, and forecasts were generated over the subsequent 25-observation window. Given the total data set length of 2,609 observations, the final nine observations were also forecasted using the same rolling-window procedure.

4.3 Forecast Error Measures

For each test interval, RMSE performance metrics were used. Subsequently, the weighted averages of these six intervals were calculated to obtain the finalized performance metrics.

4.3.1 Forecast Error Measures

Similarly, RMSE is another commonly used evaluation metric that represents the square root of the Mean Squared Error (MSE). It provides interpretable measure of error in the same unit as the original data, making it more intuitive when assessing the magnitude of prediction errors. Mathematically, it is expressed as:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4.1}$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value, and N is the total number of observations. RMSE is particularly useful when large errors are especially undesirable, as it amplifies their effect due to the squaring operation. A lower RMSE value indicates better model performance in terms of predictive accuracy.

5. OUT-OF-SAMPLE FORECASTING

This section focuses on the out-of-sample results of the models, presenting a comparative evaluation based on their forecasting performance. Tables 23-26 report the results obtained using modeling techniques similar to those employed in the study by Gu, Kelly, and Xiu (2019). The evaluation of model performance is performed using RMSE metric, as described in Section 4.3.1, and the results are reported separately for the Expanding Window and Rolling Window approaches.

In a model-level comparison, excluding the USD / TRY series, the PCR and FNN1 architectures emerge as the most successful, producing the lowest RMSE values. This ranking persists in both the forecasts for one day and the forecast for five days and in the expanding-window and rolling-window evaluation schemes. Although relative order can change slightly by currency, the RMSE outcomes remain tightly clustered.

Within the three-hidden-layer class, FNN3 outperforms FNN2, suggesting that, under a pyramidal design, a higher neuron count per layer enhances predictive accuracy. The AR and PCA-VAR models follow FNN2 and FNN3, with their RMSE results nearly indistinguishable and only marginally varying by currency. Finally, the deepest architectures, FNN4 and FNN5, with six and seven hidden layers, respectively, produce the highest RMSE values and thus rank lowest in forecasting performance.

From a currency-specific perspective, USD / TRY, which exhibits the highest standard deviation among the sampled exchange rates, also yields the highest RMSE values. Within the USD/TRY series, the AR and PCA-VAR models consistently produce the lowest RMSEs across all filtering schemes. These are followed by PCR models, for which the expanding-window implementation outperforms its rolling-window counterpart. The FNN1 architecture, whose hyperparameters are optimized via iterative grid search, achieves RMSE of 3.00 and 3.08 under the expanding and rolling-window frameworks, respectively, placing it immediately behind the PCR models. In particular, the poorest performance is observed in configurations with fixed (non-optimized) hyperparameters, which produce the highest RMSE values.

The second currency in the sample, USD/INR, proved to be the most robust, exhibiting the lowest standard deviation and the best overall forecast accuracy. These model-level findings remain valid, and in the five-day forecast exercise the superior performance of the PCR model becomes particularly pronounced.

In terms of the third currency, USD/MXN, the results again align closely with the model expectations, and distinct performance differences emerge between the competing architectures. In particular, in the five-day advance context, the AR and PCA-VAR models produce the highest RMSE values, both under the expansion window and the rolling window evaluations, indicating comparatively poorer predictive accuracy compared to the other methods.

A similar performance pattern is observed for the remaining two currencies, USD/ZAR and USD/BRL. In both cases, the PCR and FNN1 models outperform the other architectures. Overall, the forecast results for the one-day-ahead adhere to the prevailing trend: for both USD/ZAR and USD/BRL, the AR and PCA-VAR models achieve lower RMSE values than FNN2. However, this relative ordering does not hold in the five-day forecast exercise.

From the evaluation window perspective, the forecasts for one day generated under the expanding-window framework generally outperform those produced by the rolling-window approach. This advantage becomes even clearer when examined at the model level or on a currency-by-currency basis. In contrast, in the five-day forecasting exercise, the rolling window methodology consistently yields superior results compared to the expanding-window configuration. Finally, when comparing one-day-ahead to five-day-ahead forecasts, the former achieve better predictive accuracy across all currencies and window strategies. In addition, performance differences between models become more pronounced in the five-day setting.

6. CONCLUSION

This study evaluated the predictive performance of various time series and machine learning models, including AR, PCA-VAR, PCR, and FNN in modeling the implied volatility surfaces of five emerging market currency options.

Empirical analysis demonstrates that, across both expanding-window and rolling window frameworks and for both one-day-ahead and five-day-ahead forecasts, the PCR and FNN1 models consistently outperform all other approaches. In terms of performance ranking, these are followed by the three-hidden-layer architectures FNN3 and FNN2, respectively. In contrast, FNN models with fixed hyperparameters and six or seven hidden layers uniformly exhibit inferior performance across all currency pairs, most notably for high-volatility series such as USD/TRY.

The primary driver of model-specific performance differences between currencies appears to be the variation in their standard deviations. In particular, TRY has experienced significant macroeconomic deterioration and pronounced volatility over the past decade, increasing its standard deviation and making it comparatively more challenging to calibrate high-performance forecasting models. Consequently, the forecast accuracy for TRY-based series tends to be lower than that observed for other currencies.

The main contribution of this study lies in offering a comprehensive model-based and day-ahead comparison for pricing and forecasting implied volatility surfaces, which play a critical role in the financial and industrial sectors of emerging market economies. By benchmarking the forecasting accuracy of different model classes, this study contributes to the literature on volatility modeling and provides practical insights for financial practitioners managing risk in currency derivatives markets.

Despite the robustness of the findings, a key limitation is that the models utilized rely exclusively on historical volatility surface data. Future research can build on this work by integrating macroeconomic indicators, geopolitical risks, and other exogenous variables to enrich model input and potentially improve predictive performance. Such improvements could lead to a more nuanced understanding of the drivers of implied volatility and support more effective risk management strategies in dynamic financial environments.

REFERENCES

[1] F. Black and M. Scholes, "The pricing of options and corporate liabilities," *Journal of Political Economy*, vol. 81, no. 3, pp. 637–654, 1973.

[2] R. C. Merton, "Option pricing when underlying stock returns are discontinuous," *Journal of Financial Economics*, vol. 3, no. 1–2, pp. 125–144, 1976.

[3] J. C. Cox and S. A. Ross, "The valuation of options for alternative stochastic processes," *Journal of Financial Economics*, vol. 3, no. 1-2, pp. 145–166, 1976.

[4] J. Hull and A. White, "The pricing of options on assets with stochastic volatilities," *The Journal of Finance*, vol. 42, no. 2, pp. 281–300, 1987.

[5] S. L. Heston, "A closed-form solution for options with stochastic volatility with applications to bond and currency options," *The Review of Financial Studies*, vol. 6, no. 2, pp. 327–343, 1993.

[6] D. S. Bates, "Jumps and stochastic volatility: Exchange rate processes implicit in deutsche mark options," *The Review of Financial Studies*, vol. 9, no. 1, pp. 69–107, 1996.

[7] P. S. Hagan, D. Kumar, A. S. Lesniewski, and D. E. Woodward, "Managing smile risk," *Wilmott Magazine*, no. September, pp. 84–108, 2002.

[8] E. Derman and I. Kani, "Riding on a smile," *Risk*, vol. 7, no. 2, pp. 32–39, 1994.

[9] B. Dupire, "Pricing with a smile," *Risk*, vol. 7, no. 1, pp. 18–20, 1994.

[10] M. Rubinstein, "Implied binomial trees," *The Journal of Finance*, vol. 49, no. 3, pp. 771–818, 1994.

[11] B. Dumas, J. Fleming, and R. E. Whaley, "Implied volatility functions: Empirical tests," *Journal of Finance*, vol. 53, no. 6, pp. 2059–2106, 1998.

[12] N. A. Chriss, "Black–scholes smile correction," *Risk*, vol. 8, no. 2, pp. 61–65, 1995.

[13] J. H. Stock and M. W. Watson, "Forecasting using principal components from a large number of predictors," *Journal of the American Statistical Association*, vol. 97, no. 460, pp. 1167–1179, 2002.

[14] E. Konstantinidi, G. Skiadopoulos, and E. Tzagkaraki, "Can the evolution of implied volatility be forecasted? evidence from european and us implied volatility indices," *Journal of Banking and Finance*, vol. 32, no. 11, pp. 2401–2411, 2008.

[15] G. Chalamandaris and A. E. Tsekrekos, "Predictable dynamics in implied volatility surfaces from otc currency options," *Journal of Banking and Finance*, vol. 33, no. 4, pp. 767–778, 2009.

[16] B. Kelly and D. Xiu, "Autoencoders and the econometrics of asset pricing," *Journal of Financial Economics*, vol. 149, no. 2, pp. 275–298, 2023.

[17] B. Kelly, S. Gu, and D. Xiu, "Empirical asset pricing via machine learning," *The Review of Financial Studies*, vol. 33, no. 5, pp. 2223–2273, 2019.

[18] P. Carr and L. Wu, "Stochastic skew in currency options," *Journal of Financial Economics*, vol. 86, no. 1, pp. 213–247, 2007.

[19] G. Chalamandaris and A. E. Tsekrekos, "Predictability in implied volatility surfaces: Evidence from the euro otc fx market," *The European Journal of Finance*, vol. 20, no. 1, pp. 33–58, 2014.

[20] T. Masters, *Practical Neural Network Recipes in C++*. New York, NY: Academic Press, 1993.

[21] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proceedings of the 3rd International Conference on Learning Representations (ICLR)*, (San Diego, CA), 2015. arXiv:1412.6980.

[22] G. E. Hinton, N. Srivastava, A. Krizhevsky, I. Sutskever, and R. R. Salakhutdinov, "Improving neural networks by preventing co-adaptation of feature detectors." arXiv preprint arXiv:1207.0580, 2012.

[23] H. L. Shang and F. Kearney, "Dynamic functional time series forecasts of foreign exchange implied volatility surfaces," *International Journal of Forecasting*, vol. 38, no. 1, pp. 70–87, 2021.

APPENDICES

Table 6.1: *Summary statistics of implied volatility levels across all sample days, maturities, and moneyness levels for each of the five currency options.*

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDTRY	1 Week	10D	Call	20.44	16.97	116.94	7.33	12.93	3.27	15.01
		25D	Call	17.58	14.90	106.37	6.50	11.16	3.59	18.22
		50D	ATM	15.36	13.18	98.85	4.56	9.91	3.88	21.63
		25D	Put	14.63	12.56	97.12	4.11	9.51	4.04	23.48
		10D	Put	14.93	12.84	99.36	4.37	9.61	4.09	24.35
	2 Weeks	10D	Call	21.07	17.61	110.49	7.67	12.58	2.95	12.16
		25D	Call	18.20	15.52	99.80	6.88	10.78	3.23	14.88
		50D	ATM	15.66	13.57	91.78	5.96	9.34	3.60	18.91
		25D	Put	14.67	12.73	89.49	5.28	8.84	3.80	21.28
		10D	Put	14.63	12.62	91.34	4.99	8.84	3.90	22.69
	3 Weeks	10D	Call	21.84	18.25	103.79	8.42	12.46	2.64	9.51
		25D	Call	18.71	16.00	92.73	7.52	10.48	2.92	11.93
		50D	ATM	15.99	13.89	84.64	6.68	8.95	3.26	15.46
		25D	Put	14.90	12.91	82.50	5.68	8.45	3.45	17.55
		10D	Put	14.73	12.74	83.66	6.01	8.46	3.55	18.81

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDTRY	1 Month	10D	Call	22.74	18.94	102.36	8.82	12.74	2.49	8.09
		25D	Call	19.27	16.53	89.06	7.86	10.49	2.73	10.16
		50D	ATM	16.19	14.06	80.44	7.00	8.79	3.10	13.66
		25D	Put	14.96	13.04	78.03	4.26	8.24	3.30	15.74
		10D	Put	14.65	12.76	80.09	6.16	8.24	3.43	17.23
	3 Months	10D	Call	25.42	21.71	82.96	11.57	12.25	1.82	3.43
		25D	Call	21.08	18.25	69.97	9.77	9.76	1.92	4.04
		50D	ATM	17.18	14.94	60.98	8.23	7.73	2.17	5.83
		25D	Put	15.56	13.57	58.26	7.58	7.05	2.34	7.25
		10D	Put	14.97	12.93	58.35	7.33	6.80	2.51	8.70

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDINR	1 Week	10D	Call	7.67	6.88	32.35	3.71	3.18	3.09	13.73
		25D	Call	6.90	6.19	29.02	3.06	2.87	2.97	12.81
		50D	ATM	6.39	5.72	27.42	2.77	2.68	2.93	12.68
		25D	Put	6.25	5.63	26.76	2.89	2.62	3.04	13.43
		10D	Put	6.52	5.85	29.86	3.29	2.89	3.55	17.55
	2 Weeks	10D	Call	7.84	7.07	30.31	4.08	3.03	2.94	12.20
		25D	Call	7.02	6.34	26.70	3.46	2.70	2.79	11.26
		50D	ATM	6.44	5.83	24.34	3.14	2.48	2.75	11.02
		25D	Put	6.26	5.65	23.52	3.24	2.41	2.84	11.49
		10D	Put	6.46	5.84	24.56	3.68	2.55	3.10	13.18
	3 Weeks	10D	Call	8.02	7.22	29.56	4.33	2.98	2.90	11.92
		25D	Call	7.15	6.48	25.89	3.88	2.63	2.75	10.86
		50D	ATM	6.51	5.89	23.28	3.52	2.38	2.70	10.44
		25D	Put	6.31	5.72	22.32	3.55	2.30	2.77	10.72
		10D	Put	6.45	5.87	22.91	3.82	2.38	2.99	12.13

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDINR	1 Month	10D	Call	8.18	7.39	29.70	4.62	3.02	2.86	11.60
		25D	Call	7.27	6.58	25.41	4.07	2.59	2.69	10.33
		50D	ATM	6.56	5.94	22.53	3.68	2.31	2.62	9.71
		25D	Put	6.32	5.73	21.27	3.68	2.20	2.65	9.76
		10D	Put	6.41	5.83	21.58	3.90	2.27	2.85	11.01
	3 Months	10D	Call	9.20	8.42	30.35	5.74	3.02	2.50	8.62
		25D	Call	7.95	7.29	24.75	4.92	2.48	2.31	7.22
		50D	ATM	6.97	6.42	21.02	4.36	2.11	2.26	6.71
		25D	Put	6.61	6.10	19.25	4.34	1.94	2.30	6.74
		10D	Put	6.67	6.13	19.03	4.37	1.97	2.52	8.10

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDMXN	1 Week	10D	Call	14.44	13.44	69.44	5.29	6.10	4.12	26.80
		25D	Call	13.26	12.30	64.19	4.61	5.61	4.04	26.24
		50D	ATM	12.31	11.38	58.64	4.23	5.12	3.82	24.23
		25D	Put	11.86	11.00	55.04	3.99	4.80	3.59	22.08
		10D	Put	11.93	11.10	53.38	4.41	4.65	3.39	20.27
	2 Weeks	10D	Call	14.74	13.87	60.52	5.95	5.44	3.59	21.24
		25D	Call	13.37	12.57	54.91	5.09	4.93	3.45	20.44
		50D	ATM	12.26	11.51	48.98	4.52	4.44	3.18	18.24
		25D	Put	11.73	11.03	45.18	4.37	4.13	2.93	16.16
		10D	Put	11.80	11.10	43.72	4.68	4.01	2.78	14.64
	3 Weeks	10D	Call	14.88	14.12	54.75	6.44	4.93	3.16	17.71
		25D	Call	13.47	12.78	49.29	5.54	4.42	2.97	16.62
		50D	ATM	12.24	11.58	43.39	4.84	3.95	2.65	14.13
		25D	Put	11.67	11.04	39.66	4.62	3.67	2.39	12.02
		10D	Put	11.63	11.02	37.94	4.67	3.56	2.19	10.13

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDMXN	1 Month	10D	Call	15.13	14.48	51.26	6.72	4.58	2.78	14.83
		25D	Call	13.55	12.99	45.72	5.84	4.10	2.57	13.37
		50D	ATM	12.21	11.66	39.63	5.04	3.64	2.24	10.85
		25D	Put	11.56	10.98	35.83	4.73	3.37	1.98	8.89
		10D	Put	11.49	10.91	34.24	4.80	3.28	1.84	7.66
	3 Months	10D	Call	16.02	15.69	37.52	8.56	3.50	1.55	6.51
		25D	Call	14.00	13.73	32.48	7.19	3.08	1.28	5.06
		50D	ATM	12.25	11.96	26.91	5.99	2.69	0.90	3.11
		25D	Put	11.46	11.16	23.82	5.55	2.49	0.67	1.95
		10D	Put	11.39	11.15	22.65	5.61	2.44	0.60	1.54

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDZAR	1 Week	10D	Call	18.20	17.50	45.91	9.02	4.55	1.48	4.31
		25D	Call	16.62	16.10	43.97	8.16	4.05	1.52	5.24
		50D	ATM	15.41	14.95	42.92	7.57	3.73	1.54	5.81
		25D	Put	14.93	14.46	41.66	7.20	3.64	1.48	5.34
		10D	Put	15.32	14.68	41.21	7.32	3.91	1.39	3.82
	2 Weeks	10D	Call	18.48	17.96	44.35	10.50	4.03	1.29	3.71
		25D	Call	16.85	16.48	39.76	9.43	3.61	1.20	3.55
		50D	ATM	15.46	15.16	35.99	8.05	3.31	1.12	3.25
		25D	Put	14.87	14.52	34.78	8.15	3.21	1.10	3.10
		10D	Put	15.03	14.57	35.63	8.31	3.36	1.12	2.54
	3 Weeks	10D	Call	18.76	18.33	40.62	10.84	3.66	1.02	2.78
		25D	Call	17.07	16.74	35.94	9.67	3.28	0.86	2.23
		50D	ATM	15.56	15.31	32.16	8.62	3.00	0.73	1.74
		25D	Put	14.89	14.66	30.90	8.24	2.90	0.71	1.52
		10D	Put	14.92	14.64	31.61	8.33	2.98	0.76	1.37

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDZAR	1 Month	10D	Call	19.08	18.70	38.73	11.49	3.47	0.98	2.72
		25D	Call	17.23	16.92	34.18	10.06	3.12	0.76	1.86
		50D	ATM	15.57	15.34	30.39	9.01	2.84	0.60	1.26
		25D	Put	14.81	14.63	28.82	8.47	2.74	0.55	1.30
		10D	Put	14.78	14.55	29.09	8.52	2.80	0.61	0.94
	3 Months	10D	Call	20.24	19.74	33.38	13.60	2.86	0.68	1.05
		25D	Call	17.85	17.53	28.22	11.59	2.54	0.41	0.55
		50D	ATM	15.76	15.68	24.30	9.85	2.31	0.15	0.27
		25D	Put	14.83	14.88	23.90	9.06	2.24	0.02	0.13
		10D	Put	14.67	14.73	23.70	8.98	2.27	0.09	0.06

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDBRL	1 Week	10D	Call	19.05	18.35	55.30	8.01	5.71	1.22	3.26
		25D	Call	17.64	16.99	51.12	7.13	5.34	1.22	3.30
		50D	ATM	16.63	16.02	46.53	6.57	5.08	1.16	2.95
		25D	Put	16.20	15.63	43.61	6.40	4.98	1.10	2.57
		10D	Put	16.48	15.81	42.81	6.53	5.06	1.02	2.12
	2 Weeks	10D	Call	19.07	18.50	50.33	8.79	5.23	1.05	2.63
		25D	Call	17.64	17.11	44.81	7.96	4.85	0.90	1.85
		50D	ATM	16.49	16.01	39.84	7.30	4.57	0.79	1.18
		25D	Put	15.95	15.46	36.71	6.96	4.45	0.71	0.77
		10D	Put	16.03	15.62	35.59	6.91	4.47	0.69	0.56
	3 Weeks	10D	Call	19.10	18.60	43.74	9.29	4.85	0.70	0.80
		25D	Call	17.65	17.22	39.55	8.43	4.52	0.61	0.47
		50D	ATM	16.40	16.02	35.10	7.65	4.27	0.52	0.07
		25D	Put	15.81	15.40	32.47	7.37	4.14	0.48	-0.14
		10D	Put	15.76	15.33	31.98	7.35	4.15	0.49	-0.18

Currency	Maturity	Delta	Option Type	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
USDBRL	1 Month	10D	Call	19.35	18.82	42.32	9.96	4.79	0.67	0.51
		25D	Call	17.75	17.33	37.83	8.96	4.46	0.57	0.24
		50D	ATM	16.37	16.00	33.13	8.07	4.19	0.50	-0.04
		25D	Put	15.69	15.33	30.58	7.72	4.05	0.48	-0.20
		10D	Put	15.59	15.18	30.16	7.70	4.03	0.50	-0.25
	3 Months	10D	Call	20.06	19.89	33.19	11.57	4.04	0.37	-0.34
		25D	Call	17.93	17.83	28.60	10.53	3.69	0.28	-0.60
		50D	ATM	16.13	16.19	25.64	9.40	3.43	0.24	-0.80
		25D	Put	15.27	15.31	24.12	8.84	3.31	0.26	-0.88
		10D	Put	15.14	15.08	24.09	8.70	3.30	0.30	-0.89

Table 6.2: *ADF Test Results*

Targets	USDTRY		USDINR		USDMXN		USDZAR		USDBRL	
	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value
1W_C_10D	-5,45	2,62E-06	-4,37	3,35E-04	-6,61	6,36E-09	-4,98	2,38E-05	-4,02	1,31E-03
1W_P_10D	-5,74	6,37E-07	-3,9	2,04E-03	-6,34	2,81E-08	-4,63	1,16E-04	-4,44	2,57E-04
2W_C_10D	-5,16	1,08E-05	-4,13	8,62E-04	-5,78	5,17E-07	-5,09	1,49E-05	-4,39	3,06E-04
2W_P_10D	-5,85	3,64E-07	-3,66	4,71E-03	-5,57	1,49E-06	-4,74	7,15E-05	-4,5	1,98E-04
3W_C_10D	-4,82	4,94E-05	-3,98	1,53E-03	-5,29	5,67E-06	-4,86	4,09E-05	-4,38	3,21E-04
3W_P_10D	-5,47	2,39E-06	-3,84	2,48E-03	-4,31	4,33E-04	-4,22	6,14E-04	-4,22	6,14E-04
1M_C_10D	-4,53	1,75E-04	-3,88	2,17E-03	-4,75	6,77E-05	-4,97	2,55E-05	-3,67	4,52E-03
1M_P_10D	-5,32	5,00E-06	-3,63	5,29E-03	-4,16	7,66E-04	-4,38	3,22E-04	-3,66	4,65E-03
3M_C_10D	-2,73	6,91E-02	-3,38	1,18E-02	-4,6	1,29E-04	-4,56	1,53E-04	-3,85	2,48E-03
3M_P_10D	-3,84	2,51E-03	-2,77	0,06202	-3,92	1,91E-03	-3,42	1,04E-02	-3,38	1,16E-02
1W_C_25D	-5,76	5,76E-07	-4,24	5,64E-04	-6,6	6,60E-09	-5,04	1,83E-05	-4,1	9,51E-04
1W_P_25D	-5,93	2,39E-07	-3,94	1,75E-03	-6,42	1,78E-08	-4,86	4,11E-05	-4,6	1,28E-04
2W_C_25D	-5,48	2,35E-06	-4,02	1,31E-03	-5,82	4,20E-07	-5,05	1,74E-05	-4,35	3,57E-04
2W_P_25D	-5,87	3,24E-07	-3,88	2,18E-03	-5,47	2,38E-06	-4,86	4,20E-05	-4,27	5,01E-04
3W_C_25D	-5,21	8,36E-06	-4,35	3,66E-04	-5,26	6,72E-06	-4,68	9,10E-05	-4,52	1,84E-04
3W_P_25D	-5,55	1,62E-06	-4,07	1,09E-03	-4,49	2,08E-04	-4,42	2,71E-04	-4,26	5,24E-04

Targets	USDTRY		USDINR		USDMXN		USDZAR		USDBRL	
	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value	ADF Test Statistic	p-value
1M_C_25D	-4,91	3,28E-05	-4,02	1,30E-03	-4,7	8,32E-05	-4,72	7,83E-05	-4,44	2,56E-04
1M_P_25D	-5,34	4,53E-06	-3,62	5,46E-03	-4,35	3,65E-04	-4,38	3,17E-04	-3,7	4,15E-03
3M_C_25D	-3,49	8,16E-03	-3,49	8,25E-03	-4,49	2,05E-04	-4,07	1,09E-03	-3,69	4,25E-03
3M_P_25D	-3,57	6,45E-03	-3,25	1,72E-02	-4,06	1,11E-03	-3,43	1,01E-02	-3,39	1,14E-02
1W_ATM	-5,94	2,25E-07	-4,07	1,09E-03	-6,55	8,97E-09	-4,91	3,38E-05	-4,09	1,01E-03
2W_ATM	-5,79	4,93E-07	-4	1,41E-03	-5,55	1,61E-06	-4,97	2,49E-05	-4,27	4,97E-04
3W_ATM	-5,51	1,99E-06	-4	1,43E-03	-4,66	1,02E-04	-4,51	1,87E-04	-4,38	3,24E-04
1M_ATM	-5,28	6,10E-06	-3,8	2,90E-03	-4,53	1,74E-04	-4,49	2,05E-04	-3,71	4,02E-03
3M_ATM	-4,01	1,38E-03	-3,36	1,26E-02	-4,27	4,95E-04	-3,66	4,63E-03	-3,49	8,13E-03
3W_ATM	-5,51	1,99E-06	-4	1,43E-03	-4,66	1,02E-04	-4,51	1,87E-04	-4,38	3,24E-04
1M_ATM	-5,28	6,10E-06	-3,8	2,90E-03	-4,53	1,74E-04	-4,49	2,05E-04	-3,71	4,02E-03
3M_ATM	-4,01	1,38E-03	-3,36	1,26E-02	-4,27	4,95E-04	-3,66	4,63E-03	-3,49	8,13E-03

Table 6.3: *Out-of-Sample One-Day-Ahead RMSE Results for USD/TRY under Expanding-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDTRY 1W_C_10D	4,67	4,91	4,65	4,97	5,66	5,35	12,89	10,01
USDTRY 1W_P_10D	3,42	4,00	3,49	3,85	5,00	4,29	10,28	8,16
USDTRY 2W_C_10D	3,80	3,74	3,74	3,85	7,88	4,59	13,30	13,17
USDTRY 2W_P_10D	2,66	3,08	2,69	3,07	4,93	3,61	13,45	7,20
USDTRY 3W_C_10D	3,30	3,16	3,30	3,09	5,08	4,20	16,51	18,75
USDTRY 3W_P_10D	2,24	2,53	2,33	2,51	3,33	2,86	13,29	13,14
USDTRY 1M_C_10D	3,02	3,28	3,07	3,22	9,59	4,55	16,08	13,74
USDTRY 1M_P_10D	2,07	2,39	2,09	2,58	6,58	3,44	10,26	11,56
USDTRY 3M_C_10D	2,17	2,46	2,23	2,15	6,80	4,18	13,60	16,46
USDTRY 3M_P_10D	1,36	1,56	1,40	1,69	5,05	2,03	10,13	8,21
USDTRY 1W_C_25D	4,03	4,53	3,98	4,39	7,34	4,69	9,62	16,60
USDTRY 1W_P_25D	3,40	3,96	3,35	3,95	4,81	3,99	7,10	7,45
USDTRY 2W_C_25D	3,28	3,46	3,23	3,62	6,24	3,82	9,16	12,07
USDTRY 2W_P_25D	2,71	3,10	2,66	3,35	4,11	3,51	7,21	12,54
USDTRY 3W_C_25D	2,83	2,84	2,84	2,79	5,03	3,45	8,37	10,69
USDTRY 3W_P_25D	2,31	2,54	2,37	2,42	4,17	2,95	8,17	8,01
USDTRY 1M_C_25D	2,56	2,79	2,59	3,13	4,84	3,68	11,70	12,25
USDTRY 1M_P_25D	2,09	2,38	2,12	2,66	6,32	3,39	8,17	8,86
USDTRY 3M_C_25D	1,78	1,78	1,82	2,07	4,64	3,72	13,85	12,83
USDTRY 3M_P_25D	1,38	1,48	1,41	1,53	3,04	3,61	8,76	10,89
USDTRY 1W_ATM	3,61	4,24	3,58	4,06	0,11	4,12	7,73	10,42
USDTRY 2W_ATM	2,90	3,19	2,84	3,25	5,47	3,57	8,06	13,74
USDTRY 3W_ATM	2,48	2,55	2,50	2,54	3,79	3,07	7,49	10,06
USDTRY 1M_ATM	2,26	2,52	2,28	2,55	3,72	3,16	9,29	10,60
USDTRY 3M_ATM	1,50	1,50	1,55	1,71	4,86	2,24	12,24	10,03

Table 6.4: *Out-of-Sample One-Day-Ahead RMSE Results for USD/TRY under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDTRY 1W_C_10D	4,58	4,90	4,49	4,96	6,34	5,92	10,56	11,85
USDTRY 1W_P_10D	3,37	3,92	3,27	4,01	5,57	4,45	14,62	13,99
USDTRY 2W_C_10D	3,73	3,73	3,66	3,81	5,54	4,57	10,88	13,98
USDTRY 2W_P_10D	2,61	3,08	2,58	3,19	4,09	3,59	12,83	7,95
USDTRY 3W_C_10D	3,24	3,17	3,23	3,29	6,76	4,86	19,11	20,18
USDTRY 3W_P_10D	2,20	2,56	2,18	2,44	5,25	3,37	9,65	8,40
USDTRY 1M_C_10D	2,97	3,28	3,00	3,29	9,86	5,71	15,33	18,68
USDTRY 1M_P_10D	2,03	2,41	1,99	2,49	3,94	3,28	7,40	8,38
USDTRY 3M_C_10D	2,12	2,39	2,12	2,14	11,83	6,00	18,77	22,43
USDTRY 3M_P_10D	1,34	1,57	1,34	1,72	3,28	2,37	6,27	7,50
USDTRY 1W_C_25D	3,96	4,54	3,97	4,45	4,99	4,99	9,26	10,68
USDTRY 1W_P_25D	3,35	3,95	3,24	3,98	12,97	4,24	7,76	14,14
USDTRY 2W_C_25D	3,22	3,52	3,19	3,53	4,54	3,75	14,54	9,05
USDTRY 2W_P_25D	2,66	3,14	2,63	3,18	3,77	3,53	6,83	9,91
USDTRY 3W_C_25D	2,77	2,84	2,76	2,83	12,66	3,52	11,05	14,35
USDTRY 3W_P_25D	2,27	2,56	2,25	2,39	6,76	2,83	8,61	6,52
USDTRY 1M_C_25D	2,51	2,80	2,53	2,81	6,24	6,51	15,26	10,07
USDTRY 1M_P_25D	2,06	2,39	2,02	3,24	3,78	3,80	13,45	10,02
USDTRY 3M_C_25D	1,75	1,79	1,75	3,44	5,49	4,08	11,97	16,55
USDTRY 3M_P_25D	1,35	1,45	1,35	1,56	2,64	2,41	7,18	9,19
USDTRY 1W_ATM	3,55	4,27	3,49	4,05	13,60	4,36	8,43	14,54
USDTRY 2W_ATM	2,85	3,19	2,81	3,24	3,99	3,47	6,35	9,07
USDTRY 3W_ATM	2,43	2,58	2,41	2,65	3,69	2,74	5,95	12,92
USDTRY 1M_ATM	2,21	2,52	2,18	2,59	5,56	5,17	13,35	8,58
USDTRY 3M_ATM	1,47	1,53	1,47	1,61	3,50	2,81	10,42	9,76

Table 6.5: *Out-of-Sample One-Day-Ahead RMSE Results for USD/INR under Expanding-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDINR 1W_C_10D	1,05	0,51	1,02	0,52	0,96	0,64	1,30	1,22
USDINR 1W_P_10D	0,83	0,39	0,76	0,39	0,63	0,43	0,95	0,81
USDINR 2W_C_10D	0,80	0,40	0,79	0,40	0,84	0,61	1,26	1,54
USDINR 2W_P_10D	0,58	0,29	0,56	0,30	0,56	0,42	0,90	0,75
USDINR 3W_C_10D	0,62	0,33	0,61	0,33	0,59	0,43	0,91	1,37
USDINR 3W_P_10D	0,43	0,23	0,43	0,23	0,43	0,35	0,73	0,73
USDINR 1M_C_10D	0,55	0,32	0,54	0,31	0,58	0,48	1,35	1,12
USDINR 1M_P_10D	0,35	0,21	0,35	0,21	0,52	0,42	0,86	0,72
USDINR 3M_C_10D	0,39	0,22	0,39	0,21	0,42	0,28	1,13	1,17
USDINR 3M_P_10D	0,26	0,14	0,26	0,14	0,57	0,36	0,68	0,60
USDINR 1W_C_25D	0,96	0,46	0,94	0,46	0,84	0,50	1,26	1,00
USDINR 1W_P_25D	0,84	0,39	0,81	0,40	0,58	0,42	0,78	0,75
USDINR 2W_C_25D	0,72	0,36	0,71	0,36	0,81	0,43	1,19	0,99
USDINR 2W_P_25D	0,61	0,30	0,59	0,31	0,50	0,36	0,81	0,89
USDINR 3W_C_25D	0,55	0,29	0,54	0,29	0,46	0,38	0,91	0,69
USDINR 3W_P_25D	0,44	0,24	0,44	0,24	0,34	0,32	0,75	0,77
USDINR 1M_C_25D	0,48	0,27	0,48	0,27	0,59	0,32	0,86	0,92
USDINR 1M_P_25D	0,37	0,22	0,37	0,22	0,43	0,30	0,83	0,71
USDINR 3M_C_25D	0,33	0,18	0,34	0,18	0,56	0,23	0,76	0,86
USDINR 3M_P_25D	0,25	0,13	0,25	0,14	0,47	0,32	0,72	0,60
USDINR 1W_ATM	0,89	0,42	0,86	0,42	0,59	0,52	1,01	0,99
USDINR 2W_ATM	0,65	0,32	0,64	0,33	0,43	0,37	0,96	0,86
USDINR 3W_ATM	0,48	0,26	0,48	0,26	0,43	0,31	0,89	0,80
USDINR 1M_ATM	0,41	0,24	0,41	0,24	0,36	0,28	0,77	0,76
USDINR 3M_ATM	0,27	0,15	0,28	0,15	0,38	0,22	0,63	0,74

Table 6.6: *Out-of-Sample One-Day-Ahead RMSE Results for USD/INR under Rolling-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDINR 1W_C_10D	1,04	0,51	0,98	0,52	0,70	0,65	1,14	1,26
USDINR 1W_P_10D	0,81	0,39	0,78	0,39	0,61	0,45	0,94	0,76
USDINR 2W_C_10D	0,79	0,40	0,77	0,41	0,69	0,59	1,25	1,45
USDINR 2W_P_10D	0,58	0,30	0,55	0,30	0,43	0,42	0,76	0,75
USDINR 3W_C_10D	0,62	0,33	0,61	0,33	0,88	0,51	1,22	1,11
USDINR 3W_P_10D	0,42	0,23	0,41	0,23	0,49	0,40	0,81	0,70
USDINR 1M_C_10D	0,55	0,32	0,53	0,31	0,60	0,48	1,34	1,26
USDINR 1M_P_10D	0,35	0,21	0,35	0,21	0,48	0,41	0,61	0,71
USDINR 3M_C_10D	0,38	0,21	0,38	0,22	0,53	0,29	1,04	1,23
USDINR 3M_P_10D	0,26	0,13	0,25	0,14	0,60	0,42	0,67	0,67
USDINR 1W_C_25D	0,95	0,46	0,85	0,46	0,84	0,64	1,20	1,08
USDINR 1W_P_25D	0,83	0,40	0,74	0,40	0,53	0,42	0,94	0,79
USDINR 2W_C_25D	0,71	0,36	0,68	0,36	0,47	0,48	1,06	0,97
USDINR 2W_P_25D	0,60	0,30	0,57	0,31	0,49	0,37	0,91	0,81
USDINR 3W_C_25D	0,54	0,29	0,53	0,29	0,73	0,36	0,95	0,79
USDINR 3W_P_25D	0,44	0,24	0,43	0,24	0,41	0,35	0,80	0,78
USDINR 1M_C_25D	0,47	0,27	0,46	0,27	0,48	0,37	0,99	1,01
USDINR 1M_P_25D	0,37	0,22	0,36	0,22	0,51	0,29	0,79	0,73
USDINR 3M_C_25D	0,33	0,18	0,33	0,18	0,50	0,24	0,97	0,89
USDINR 3M_P_25D	0,24	0,13	0,24	0,14	0,40	0,29	0,70	0,74
USDINR 1W_ATM	0,87	0,42	0,80	0,42	0,79	0,45	0,82	0,94
USDINR 2W_ATM	0,64	0,32	0,61	0,33	0,40	0,51	0,95	1,00
USDINR 3W_ATM	0,48	0,26	0,47	0,26	0,41	0,30	0,82	0,90
USDINR 1M_ATM	0,41	0,24	0,40	0,24	0,34	0,29	0,87	0,94
USDINR 3M_ATM	0,27	0,15	0,27	0,15	0,27	0,22	0,72	0,74

Table 6.7: *Out-of-Sample One-Day-Ahead RMSE Results for USD/MXN under Expanding-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDMXN 1W_C_10D	2,77	1,04	2,86	1,06	1,61	1,40	3,44	3,14
USDMXN 1W_P_10D	2,19	0,80	2,18	0,84	1,06	0,90	2,39	1,98
USDMXN 2W_C_10D	2,13	0,83	2,12	0,81	1,63	1,22	3,38	3,33
USDMXN 2W_P_10D	1,59	0,60	1,64	0,64	0,88	0,77	1,93	2,14
USDMXN 3W_C_10D	1,81	0,65	1,78	0,67	1,65	1,11	3,16	3,43
USDMXN 3W_P_10D	1,28	0,47	1,23	0,48	0,69	0,60	2,01	2,09
USDMXN 1M_C_10D	1,56	0,63	1,58	0,62	1,44	1,41	3,60	3,93
USDMXN 1M_P_10D	1,08	0,45	1,12	0,46	0,85	0,54	1,82	1,42
USDMXN 3M_C_10D	0,94	0,39	0,95	0,39	1,42	1,17	4,23	3,63
USDMXN 3M_P_10D	0,58	0,29	0,59	0,27	0,80	0,67	2,27	2,09
USDMXN 1W_C_25D	2,59	0,95	2,66	0,95	1,60	1,06	2,81	2,72
USDMXN 1W_P_25D	2,26	0,84	2,26	0,86	1,05	0,92	1,90	2,19
USDMXN 2W_C_25D	1,93	0,72	1,92	0,74	1,17	0,93	2,69	2,73
USDMXN 2W_P_25D	1,63	0,62	1,60	0,62	0,94	0,74	1,78	1,93
USDMXN 3W_C_25D	1,64	0,60	1,64	0,59	1,00	0,85	2,97	2,77
USDMXN 3W_P_25D	1,32	0,50	1,31	0,50	0,86	0,61	1,96	2,29
USDMXN 1M_C_25D	1,41	0,55	1,42	0,55	1,33	0,92	2,86	2,63
USDMXN 1M_P_25D	1,14	0,45	1,17	0,45	0,82	0,53	1,93	2,37
USDMXN 3M_C_25D	0,82	0,34	0,83	0,34	1,20	0,96	3,12	3,10
USDMXN 3M_P_25D	0,62	0,28	0,62	0,27	0,89	0,70	2,08	2,29
USDMXN 1W_ATM	2,40	0,89	2,44	0,90	1,28	0,95	1,95	2,27
USDMXN 2W_ATM	1,75	0,66	1,73	0,67	0,97	1,03	2,37	2,43
USDMXN 3W_ATM	1,45	0,54	1,45	0,54	0,86	0,66	2,29	2,13
USDMXN 1M_ATM	1,24	0,50	1,27	0,49	0,73	0,61	2,63	2,53
USDMXN 3M_ATM	0,69	0,29	0,70	0,30	0,90	0,76	1,85	2,32

Table 6.8: *Out-of-Sample One-Day-Ahead RMSE Results for USD/MXN under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDMXN 1W_C_10D	2,71	1,04	2,71	1,06	2,03	1,55	3,42	3,51
USDMXN 1W_P_10D	2,14	0,81	2,10	0,83	0,96	0,91	2,19	2,32
USDMXN 2W_C_10D	2,09	0,84	2,12	0,82	2,26	1,51	3,62	3,71
USDMXN 2W_P_10D	1,56	0,62	1,54	0,63	0,80	0,74	1,97	2,11
USDMXN 3W_C_10D	1,78	0,65	1,77	0,65	1,43	1,14	3,16	3,60
USDMXN 3W_P_10D	1,25	0,47	1,22	0,48	0,64	0,58	1,61	2,29
USDMXN 1M_C_10D	1,54	0,62	1,55	0,62	1,72	1,53	3,10	3,50
USDMXN 1M_P_10D	1,06	0,46	1,05	0,47	0,72	0,52	1,77	2,02
USDMXN 3M_C_10D	0,93	0,39	0,93	0,39	1,43	1,13	2,86	3,43
USDMXN 3M_P_10D	0,57	0,29	0,56	0,27	0,99	0,69	2,14	2,12
USDMXN 1W_C_25D	2,54	0,95	2,58	0,95	1,69	1,12	2,96	2,94
USDMXN 1W_P_25D	2,22	0,85	2,13	0,87	1,46	0,92	2,33	2,04
USDMXN 2W_C_25D	1,89	0,73	1,91	0,74	1,37	1,04	3,03	3,11
USDMXN 2W_P_25D	1,60	0,62	1,58	0,63	0,96	0,70	1,79	2,37
USDMXN 3W_C_25D	1,63	0,60	1,61	0,59	1,06	0,89	2,77	2,85
USDMXN 3W_P_25D	1,30	0,50	1,28	0,50	0,61	0,55	2,42	2,38
USDMXN 1M_C_25D	1,39	0,55	1,38	0,55	1,07	0,85	3,08	3,14
USDMXN 1M_P_25D	1,12	0,45	1,12	0,46	0,62	0,57	2,04	2,23
USDMXN 3M_C_25D	0,81	0,34	0,81	0,34	1,00	0,97	3,15	3,19
USDMXN 3M_P_25D	0,61	0,28	0,61	0,28	0,75	0,64	2,08	2,26
USDMXN 1W_ATM	2,35	0,89	2,30	0,90	1,25	1,01	2,35	2,55
USDMXN 2W_ATM	1,71	0,66	1,75	0,68	0,97	0,80	2,42	2,04
USDMXN 3W_ATM	1,43	0,54	1,40	0,54	0,98	0,70	2,35	2,73
USDMXN 1M_ATM	1,22	0,49	1,22	0,50	0,80	0,67	2,57	2,60
USDMXN 3M_ATM	0,68	0,29	0,67	0,30	1,05	0,63	2,63	2,58

Table 6.9: *Out-of-Sample One-Day-Ahead RMSE Results for USD/ZAR under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDZAR 1W_C_10D	1,94	0,94	1,89	0,91	1,41	1,22	3,32	3,70
USDZAR 1W_P_10D	1,60	0,79	1,57	0,72	1,22	0,83	2,39	2,20
USDZAR 2W_C_10D	1,57	0,74	1,53	0,73	1,40	1,09	3,38	3,20
USDZAR 2W_P_10D	1,27	0,58	1,24	0,56	1,02	0,94	2,86	2,53
USDZAR 3W_C_10D	1,28	0,65	1,27	0,69	1,33	1,38	3,21	3,82
USDZAR 3W_P_10D	0,98	0,45	0,97	0,45	1,11	1,02	2,80	3,10
USDZAR 1M_C_10D	1,22	0,60	1,19	0,53	1,34	1,03	3,40	4,17
USDZAR 1M_P_10D	0,90	0,44	0,89	0,42	1,04	1,03	2,65	3,23
USDZAR 3M_C_10D	0,76	0,34	0,77	0,33	1,20	0,98	2,89	3,36
USDZAR 3M_P_10D	0,52	0,24	0,53	0,23	1,29	1,31	2,85	2,61
USDZAR 1W_C_25D	1,82	0,86	1,82	0,83	1,17	1,12	3,28	3,39
USDZAR 1W_P_25D	1,62	0,75	1,61	0,73	1,25	0,97	2,69	2,53
USDZAR 2W_C_25D	1,44	0,67	1,40	0,66	1,12	0,92	3,31	2,83
USDZAR 2W_P_25D	1,26	0,57	1,24	0,56	1,04	0,91	2,44	2,65
USDZAR 3W_C_25D	1,16	0,52	1,12	0,57	1,22	1,18	3,40	3,10
USDZAR 3W_P_25D	0,98	0,41	0,96	0,46	1,05	0,97	2,99	3,30
USDZAR 1M_C_25D	1,09	0,53	1,06	0,51	1,08	0,89	3,06	3,82
USDZAR 1M_P_25D	0,92	0,42	0,90	0,39	1,12	1,01	2,73	3,35
USDZAR 3M_C_25D	0,65	0,31	0,65	0,27	1,11	0,83	3,07	2,42
USDZAR 3M_P_25D	0,52	0,22	0,52	0,22	1,25	1,13	2,83	2,54
USDZAR 1W_ATM	1,71	0,80	1,70	0,76	1,22	0,94	2,84	2,83
USDZAR 2W_ATM	1,33	0,60	1,31	0,59	1,16	0,84	2,72	2,76
USDZAR 3W_ATM	1,04	0,45	1,02	0,50	1,04	1,13	2,84	3,23
USDZAR 1M_ATM	0,97	0,46	0,97	0,43	1,07	0,94	2,96	3,35
USDZAR 3M_ATM	0,57	0,23	0,57	0,23	1,16	1,33	3,12	2,63

Table 6.10: *Out-of-Sample One-Day-Ahead RMSE Results for USD/ZAR under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDZAR 1W_C_10D	1,89	0,97	1,85	0,92	1,46	1,15	3,81	3,00
USDZAR 1W_P_10D	1,58	0,76	1,50	0,71	1,02	0,80	2,67	2,67
USDZAR 2W_C_10D	1,55	0,79	1,51	0,73	1,24	1,00	3,42	3,47
USDZAR 2W_P_10D	1,25	0,58	1,22	0,55	0,98	0,79	2,37	2,86
USDZAR 3W_C_10D	1,26	0,64	1,25	0,71	1,41	1,21	3,08	4,41
USDZAR 3W_P_10D	0,96	0,45	0,94	0,46	0,94	0,90	2,77	3,00
USDZAR 1M_C_10D	1,20	0,62	1,18	0,57	1,17	0,97	3,30	4,05
USDZAR 1M_P_10D	0,89	0,44	0,88	0,41	1,04	1,10	2,59	2,88
USDZAR 3M_C_10D	0,75	0,35	0,75	0,32	1,16	0,80	3,63	3,05
USDZAR 3M_P_10D	0,51	0,24	0,51	0,23	1,35	1,17	2,85	3,35
USDZAR 1W_C_25D	1,79	0,85	1,75	0,82	1,32	1,04	3,21	3,70
USDZAR 1W_P_25D	1,59	0,76	1,53	0,73	1,09	0,89	2,91	2,96
USDZAR 2W_C_25D	1,43	0,70	1,39	0,67	1,11	0,99	2,86	3,59
USDZAR 2W_P_25D	1,24	0,57	1,24	0,57	1,02	0,85	2,79	2,57
USDZAR 3W_C_25D	1,14	0,51	1,12	0,59	1,45	0,94	3,74	4,18
USDZAR 3W_P_25D	0,97	0,41	0,96	0,46	1,25	1,01	3,32	3,27
USDZAR 1M_C_25D	1,08	0,54	1,06	0,49	1,00	0,94	3,16	3,26
USDZAR 1M_P_25D	0,90	0,43	0,89	0,41	0,91	0,92	2,80	2,91
USDZAR 3M_C_25D	0,64	0,30	0,64	0,28	0,93	0,73	2,73	2,95
USDZAR 3M_P_25D	0,51	0,23	0,52	0,22	1,38	0,95	3,07	2,72
USDZAR 1W_ATM	1,68	0,79	1,64	0,76	1,07	0,97	3,09	3,09
USDZAR 2W_ATM	1,30	0,60	1,31	0,60	1,13	0,84	3,07	2,91
USDZAR 3W_ATM	1,03	0,43	1,03	0,50	1,11	0,96	3,01	3,19
USDZAR 1M_ATM	0,97	0,46	0,95	0,43	1,04	0,96	2,74	3,01
USDZAR 3M_ATM	0,56	0,24	0,56	0,24	1,11	0,97	2,70	3,06

Table 6.11: *Out-of-Sample One-Day-Ahead RMSE Results for USD/BRL under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDBRL 1W_C_10D	2,46	1,44	2,44	1,47	1,96	1,78	4,76	5,59
USDBRL 1W_P_10D	2,03	1,32	2,03	1,34	2,85	1,44	4,44	4,81
USDBRL 2W_C_10D	1,99	0,85	2,04	0,87	1,35	1,32	5,30	5,03
USDBRL 2W_P_10D	1,44	0,77	1,48	0,79	1,45	1,26	4,04	4,02
USDBRL 3W_C_10D	1,54	0,63	1,51	0,63	1,59	1,09	4,43	4,90
USDBRL 3W_P_10D	1,14	0,55	1,14	0,58	1,29	1,43	4,36	4,33
USDBRL 1M_C_10D	1,38	0,62	1,39	0,63	2,08	1,07	5,04	5,40
USDBRL 1M_P_10D	1,03	0,53	1,05	0,54	1,35	1,27	4,35	4,47
USDBRL 3M_C_10D	0,89	0,35	0,89	0,39	1,33	0,92	4,00	4,80
USDBRL 3M_P_10D	0,63	0,29	0,65	0,32	2,29	1,59	4,31	4,65
USDBRL 1W_C_25D	2,32	1,38	2,30	1,39	2,01	1,83	5,17	5,21
USDBRL 1W_P_25D	2,07	1,35	2,04	1,36	1,80	1,86	3,90	4,59
USDBRL 2W_C_25D	1,80	0,81	1,83	0,84	1,48	1,27	4,48	4,53
USDBRL 2W_P_25D	1,51	0,78	1,50	0,80	1,35	1,25	4,30	4,07
USDBRL 3W_C_25D	1,42	0,60	1,41	0,60	1,12	0,99	4,20	4,33
USDBRL 3W_P_25D	1,17	0,55	1,16	0,56	1,41	1,38	4,43	4,38
USDBRL 1M_C_25D	1,27	0,58	1,27	0,57	1,17	1,03	4,37	4,84
USDBRL 1M_P_25D	1,04	0,51	1,06	0,51	2,27	1,59	4,30	4,74
USDBRL 3M_C_25D	0,79	0,32	0,82	0,32	1,35	0,83	3,97	4,55
USDBRL 3M_P_25D	0,63	0,29	0,65	0,30	2,26	1,43	4,63	3,95
USDBRL 1W_ATM	2,17	1,35	2,15	1,36	1,87	1,69	4,80	5,08
USDBRL 2W_ATM	1,63	0,79	1,63	0,80	1,88	1,12	4,80	4,16
USDBRL 3W_ATM	1,27	0,57	1,27	0,58	1,15	1,19	3,98	4,29
USDBRL 1M_ATM	1,13	0,53	1,13	0,54	1,67	1,00	3,91	5,10
USDBRL 3M_ATM	0,68	0,30	0,70	0,29	1,56	1,28	4,27	4,40

Table 6.12: *Out-of-Sample One-Day-Ahead RMSE Results for USD/BRL under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDBRL 1W_C_10D	2,42	1,46	2,39	1,49	2,20	1,78	4,91	5,34
USDBRL 1W_P_10D	2,00	1,35	1,96	1,34	2,02	1,45	4,57	4,05
USDBRL 2W_C_10D	1,96	0,87	2,02	0,90	2,46	1,30	5,29	5,87
USDBRL 2W_P_10D	1,43	0,78	1,42	0,80	1,67	1,25	4,11	4,25
USDBRL 3W_C_10D	1,52	0,64	1,48	0,64	1,57	1,01	5,03	4,68
USDBRL 3W_P_10D	1,13	0,56	1,12	0,58	1,43	1,41	4,12	4,90
USDBRL 1M_C_10D	1,37	0,66	1,33	0,64	1,97	1,02	4,73	4,97
USDBRL 1M_P_10D	1,02	0,53	1,00	0,57	1,64	1,14	4,48	4,81
USDBRL 3M_C_10D	0,88	0,35	0,89	0,39	1,27	0,95	4,21	4,16
USDBRL 3M_P_10D	0,63	0,29	0,64	0,30	1,97	1,74	4,53	4,73
USDBRL 1W_C_25D	2,28	1,38	2,25	1,41	2,17	1,67	4,74	5,56
USDBRL 1W_P_25D	2,04	1,35	2,00	1,37	2,01	1,57	3,82	5,06
USDBRL 2W_C_25D	1,78	0,81	1,80	0,85	1,57	1,37	4,85	4,84
USDBRL 2W_P_25D	1,49	0,78	1,50	0,79	1,19	1,13	4,60	4,24
USDBRL 3W_C_25D	1,40	0,61	1,38	0,59	2,53	1,16	4,48	4,92
USDBRL 3W_P_25D	1,16	0,56	1,13	0,56	1,35	1,00	4,34	4,57
USDBRL 1M_C_25D	1,26	0,58	1,23	0,57	1,50	1,07	4,57	4,47
USDBRL 1M_P_25D	1,03	0,52	1,02	0,51	1,52	1,38	4,53	4,59
USDBRL 3M_C_25D	0,78	0,32	0,79	0,32	1,56	1,27	4,54	4,65
USDBRL 3M_P_25D	0,62	0,30	0,63	0,30	1,81	1,51	4,42	4,62
USDBRL 1W_ATM	2,14	1,35	2,09	1,36	2,06	1,72	4,89	5,12
USDBRL 2W_ATM	1,60	0,79	1,61	0,81	1,64	1,35	4,41	4,80
USDBRL 3W_ATM	1,25	0,58	1,24	0,58	1,44	1,09	4,69	4,49
USDBRL 1M_ATM	1,12	0,53	1,09	0,54	1,82	1,27	3,93	4,48
USDBRL 3M_ATM	0,67	0,30	0,68	0,30	1,67	1,37	4,73	4,47

Table 6.13: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/TRY under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDTRY 1W_C_10D	7,28	10,62	7,15	10,74	10,55	10,34	19,48	19,24
USDTRY 1W_P_10D	4,95	8,31	4,95	8,46	10,60	8,35	11,06	9,27
USDTRY 2W_C_10D	6,04	9,23	6,00	9,69	9,21	9,19	12,86	18,92
USDTRY 2W_P_10D	3,97	7,30	3,99	7,95	7,80	7,29	9,40	11,00
USDTRY 3W_C_10D	5,36	7,90	5,38	8,19	7,68	8,01	15,39	15,19
USDTRY 3W_P_10D	3,33	6,30	3,41	6,58	6,46	6,28	9,83	10,82
USDTRY 1M_C_10D	5,04	7,82	5,03	8,41	13,28	8,14	16,02	16,61
USDTRY 1M_P_10D	3,10	6,14	3,15	6,12	11,81	7,03	8,98	9,05
USDTRY 3M_C_10D	3,81	5,53	3,86	5,33	6,73	6,05	16,07	20,03
USDTRY 3M_P_10D	2,20	3,80	2,22	3,70	8,80	4,34	8,11	11,67
USDTRY 1W_C_25D	6,18	9,71	6,14	10,33	9,15	9,35	11,74	13,32
USDTRY 1W_P_25D	5,11	8,31	5,08	8,87	8,63	8,05	9,23	14,29
USDTRY 2W_C_25D	5,14	8,06	5,08	8,78	9,48	8,40	13,37	12,42
USDTRY 2W_P_25D	4,08	7,27	4,05	8,00	7,97	7,12	9,17	8,75
USDTRY 3W_C_25D	4,55	7,46	4,57	7,25	7,28	6,89	10,33	13,25
USDTRY 3W_P_25D	3,56	6,20	3,58	7,72	6,55	6,09	8,41	8,70
USDTRY 1M_C_25D	4,19	6,62	4,19	6,87	6,88	6,74	13,58	15,97
USDTRY 1M_P_25D	3,20	5,87	3,23	5,78	6,62	6,23	8,53	9,54
USDTRY 3M_C_25D	3,07	4,50	3,13	5,43	6,47	5,07	12,20	16,83
USDTRY 3M_P_25D	2,26	3,82	2,29	3,80	4,34	4,16	8,30	10,31
USDTRY 1W_ATM	5,47	8,57	5,47	9,40	8,39	8,60	10,84	14,74
USDTRY 2W_ATM	4,42	7,72	4,37	8,27	9,30	7,42	9,91	14,55
USDTRY 3W_ATM	3,86	6,87	3,89	7,18	6,42	6,52	14,41	10,52
USDTRY 1M_ATM	3,49	6,12	3,48	6,34	6,99	6,71	9,84	11,39
USDTRY 3M_ATM	2,49	3,91	2,55	4,06	5,28	4,16	12,00	11,08

Table 6.14: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/TRY under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDTRY 1W_C_10D	7,15	10,63	7,03	10,76	12,35	10,18	13,93	15,05
USDTRY 1W_P_10D	4,87	8,33	4,83	8,33	8,51	8,18	10,74	11,95
USDTRY 2W_C_10D	5,93	9,21	5,88	9,12	8,99	9,13	19,84	12,46
USDTRY 2W_P_10D	3,90	7,25	3,87	7,82	8,21	7,25	9,46	9,62
USDTRY 3W_C_10D	5,26	7,94	5,28	8,32	10,75	7,98	11,78	15,56
USDTRY 3W_P_10D	3,27	6,30	3,26	6,72	6,67	6,21	13,80	9,19
USDTRY 1M_C_10D	4,95	7,87	4,95	22,39	9,23	7,92	16,22	13,99
USDTRY 1M_P_10D	3,05	6,12	3,03	6,21	6,84	6,68	8,85	9,38
USDTRY 3M_C_10D	3,74	5,66	3,75	5,49	8,99	6,25	21,62	17,81
USDTRY 3M_P_10D	2,16	3,80	2,17	3,71	4,72	4,33	7,53	8,11
USDTRY 1W_C_25D	6,08	9,44	6,00	10,05	9,39	9,60	12,49	11,71
USDTRY 1W_P_25D	5,02	8,22	4,95	9,10	8,61	8,11	10,62	11,07
USDTRY 2W_C_25D	5,04	8,07	5,01	9,18	8,26	8,00	10,27	16,69
USDTRY 2W_P_25D	4,01	7,47	3,99	8,08	7,50	7,24	10,69	13,45
USDTRY 3W_C_25D	4,47	7,49	4,47	7,26	7,31	6,86	12,58	10,38
USDTRY 3W_P_25D	3,49	6,25	3,46	7,39	6,65	6,47	13,22	8,77
USDTRY 1M_C_25D	4,12	6,59	4,10	6,85	7,27	6,81	11,87	11,51
USDTRY 1M_P_25D	3,14	5,85	3,13	5,97	6,27	6,52	9,25	9,39
USDTRY 3M_C_25D	3,02	4,51	3,02	5,08	5,61	4,75	11,96	16,04
USDTRY 3M_P_25D	2,22	3,89	2,22	3,84	4,82	4,08	11,28	9,08
USDTRY 1W_ATM	5,37	8,56	5,31	10,14	14,50	8,44	15,31	10,74
USDTRY 2W_ATM	4,34	7,68	4,31	8,17	7,51	7,36	13,77	9,29
USDTRY 3W_ATM	3,78	6,52	3,77	7,53	6,77	6,82	9,32	9,56
USDTRY 1M_ATM	3,42	6,09	3,41	6,51	7,43	6,78	13,49	10,21
USDTRY 3M_ATM	2,45	3,85	2,45	4,15	4,04	4,03	9,12	12,60

Table 6.15: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/INR under Expanding-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDINR 1W_C_10D	1,80	0,98	1,71	1,09	1,02	1,00	1,47	1,42
USDINR 1W_P_10D	1,37	0,74	1,33	0,75	0,85	0,76	0,89	0,91
USDINR 2W_C_10D	1,45	0,85	1,44	0,86	0,86	0,89	1,42	1,19
USDINR 2W_P_10D	1,07	0,61	1,05	0,73	0,69	0,66	0,90	0,85
USDINR 3W_C_10D	1,18	0,72	1,18	0,87	0,91	0,75	1,18	1,26
USDINR 3W_P_10D	0,82	0,49	0,81	0,74	0,58	0,61	0,85	0,84
USDINR 1M_C_10D	1,06	0,68	1,06	0,70	0,89	0,72	1,45	1,42
USDINR 1M_P_10D	0,69	0,44	0,68	0,44	0,66	0,51	0,97	0,78
USDINR 3M_C_10D	0,78	0,50	0,78	0,57	0,72	0,53	1,24	1,13
USDINR 3M_P_10D	0,47	0,29	0,46	0,31	0,52	0,43	0,68	0,72
USDINR 1W_C_25D	1,64	0,90	1,58	0,92	0,92	0,90	1,23	1,14
USDINR 1W_P_25D	1,42	0,77	1,36	0,78	0,76	0,75	1,01	1,00
USDINR 2W_C_25D	1,31	0,76	1,29	1,07	0,81	0,78	1,24	1,21
USDINR 2W_P_25D	1,11	0,63	1,11	0,73	0,69	0,64	0,96	0,89
USDINR 3W_C_25D	1,04	0,63	1,05	0,63	0,69	0,62	1,08	1,10
USDINR 3W_P_25D	0,86	0,52	0,85	0,54	0,59	0,54	0,83	0,77
USDINR 1M_C_25D	0,92	0,58	0,92	0,60	0,76	0,59	1,13	1,02
USDINR 1M_P_25D	0,71	0,45	0,71	0,55	0,55	0,47	0,78	0,76
USDINR 3M_C_25D	0,66	0,41	0,66	0,41	0,56	0,41	1,06	0,96
USDINR 3M_P_25D	0,48	0,30	0,48	0,35	0,48	0,37	0,71	0,80
USDINR 1W_ATM	1,50	0,82	1,44	0,83	0,83	0,80	0,98	1,16
USDINR 2W_ATM	1,18	0,68	1,18	0,80	0,69	0,68	1,06	1,10
USDINR 3W_ATM	0,93	0,57	0,94	0,60	0,64	0,55	0,87	0,97
USDINR 1M_ATM	0,79	0,52	0,79	0,52	0,59	0,51	0,91	0,98
USDINR 3M_ATM	0,55	0,34	0,55	0,39	0,43	0,34	0,85	0,78

Table 6.16: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/INR under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDINR 1W_C_10D	1,76	1,02	1,66	1,06	1,13	1,01	1,57	1,30
USDINR 1W_P_10D	1,34	0,72	1,27	0,75	0,82	0,75	1,00	1,03
USDINR 2W_C_10D	1,43	0,87	1,40	0,86	0,94	0,93	1,34	1,24
USDINR 2W_P_10D	1,05	0,61	1,03	0,68	0,77	0,65	0,91	0,80
USDINR 3W_C_10D	1,17	0,73	1,14	0,83	0,80	0,76	1,37	1,18
USDINR 3W_P_10D	0,81	0,49	0,78	0,63	0,61	0,54	0,87	0,94
USDINR 1M_C_10D	1,05	0,67	1,04	0,74	0,95	0,76	1,33	1,26
USDINR 1M_P_10D	0,68	0,43	0,66	0,45	0,62	0,52	0,89	0,92
USDINR 3M_C_10D	0,77	0,50	0,77	0,59	0,63	0,52	1,33	1,16
USDINR 3M_P_10D	0,46	0,29	0,45	0,34	0,53	0,46	0,88	0,68
USDINR 1W_C_25D	1,60	0,89	1,49	0,91	0,95	0,90	1,16	1,24
USDINR 1W_P_25D	1,38	0,75	1,32	0,78	0,81	0,74	1,02	0,97
USDINR 2W_C_25D	1,28	0,76	1,24	0,92	0,83	0,78	1,05	1,06
USDINR 2W_P_25D	1,09	0,63	1,07	0,69	0,73	0,66	0,88	1,01
USDINR 3W_C_25D	1,03	0,64	1,01	0,64	0,66	0,65	1,02	1,02
USDINR 3W_P_25D	0,84	0,51	0,82	0,54	0,54	0,53	0,80	0,96
USDINR 1M_C_25D	0,91	0,59	0,90	0,59	0,71	0,61	1,10	1,12
USDINR 1M_P_25D	0,70	0,45	0,70	0,52	0,60	0,52	0,93	0,92
USDINR 3M_C_25D	0,65	0,43	0,65	0,42	0,52	0,43	0,94	1,02
USDINR 3M_P_25D	0,47	0,31	0,47	0,37	0,47	0,40	0,82	0,78
USDINR 1W_ATM	1,47	0,82	1,41	0,83	0,81	0,79	0,95	1,05
USDINR 2W_ATM	1,16	0,68	1,13	0,84	0,77	0,68	0,96	1,00
USDINR 3W_ATM	0,91	0,56	0,90	0,59	0,64	0,56	0,98	1,04
USDINR 1M_ATM	0,78	0,51	0,78	0,53	0,64	0,52	0,81	0,83
USDINR 3M_ATM	0,54	0,35	0,54	0,41	0,59	0,37	0,67	0,84

Table 6.17: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/MXN under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDMXN 1W_C_10D	5,23	2,36	5,22	2,31	2,46	2,41	3,71	3,73
USDMXN 1W_P_10D	4,03	1,82	4,08	1,92	1,77	1,81	2,43	2,41
USDMXN 2W_C_10D	4,20	1,97	4,26	2,05	2,32	2,09	3,36	4,03
USDMXN 2W_P_10D	3,08	1,50	3,16	1,59	1,54	1,44	2,39	2,27
USDMXN 3W_C_10D	3,60	1,71	3,62	1,78	1,99	1,87	3,79	3,32
USDMXN 3W_P_10D	2,52	1,25	2,50	1,19	1,16	1,18	2,20	1,97
USDMXN 1M_C_10D	3,20	1,57	3,24	1,53	2,02	1,76	3,39	3,49
USDMXN 1M_P_10D	2,16	1,16	2,21	1,04	1,09	1,04	1,82	2,11
USDMXN 3M_C_10D	2,00	1,00	2,02	1,39	1,70	1,31	3,21	3,77
USDMXN 3M_P_10D	1,20	0,68	1,21	0,67	1,04	0,86	2,15	2,06
USDMXN 1W_C_25D	4,88	2,16	4,97	2,09	2,26	2,17	3,11	2,86
USDMXN 1W_P_25D	4,19	1,86	4,17	2,01	1,83	1,87	2,44	2,35
USDMXN 2W_C_25D	3,86	1,79	3,90	1,80	1,86	1,93	3,20	2,83
USDMXN 2W_P_25D	3,21	1,51	3,23	1,51	1,74	1,47	2,31	2,30
USDMXN 3W_C_25D	3,29	1,51	3,34	1,59	1,80	1,53	3,02	2,87
USDMXN 3W_P_25D	2,67	1,24	2,69	1,26	1,26	1,19	2,29	2,29
USDMXN 1M_C_25D	2,89	1,34	2,91	1,39	1,61	1,44	3,08	2,79
USDMXN 1M_P_25D	2,28	1,10	2,31	1,09	1,20	1,11	1,98	2,07
USDMXN 3M_C_25D	1,74	0,85	1,76	0,91	1,41	1,12	2,68	2,88
USDMXN 3M_P_25D	1,27	0,67	1,28	0,72	0,98	0,80	2,11	2,14
USDMXN 1W_ATM	4,47	2,01	4,54	1,98	2,05	1,96	2,74	2,62
USDMXN 2W_ATM	3,48	1,58	3,50	1,63	1,78	1,66	2,42	2,70
USDMXN 3W_ATM	2,92	1,31	2,96	1,37	1,37	1,36	2,18	2,30
USDMXN 1M_ATM	2,52	1,17	2,54	1,17	1,33	1,28	2,50	2,87
USDMXN 3M_ATM	1,44	0,74	1,46	0,75	1,10	0,92	2,64	2,42

Table 6.18: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/MXN under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDMXN 1W_C_10D	5,12	2,35	5,03	2,31	2,52	2,44	3,43	3,73
USDMXN 1W_P_10D	3,95	1,85	3,87	1,86	1,99	1,82	2,31	2,34
USDMXN 2W_C_10D	4,12	1,96	4,13	2,02	2,32	2,14	3,93	3,29
USDMXN 2W_P_10D	3,02	1,53	3,04	1,52	1,46	1,48	2,07	2,08
USDMXN 3W_C_10D	3,54	1,74	3,53	1,71	2,18	1,82	3,24	3,50
USDMXN 3W_P_10D	2,47	1,28	2,44	1,21	1,40	1,21	2,02	2,37
USDMXN 1M_C_10D	3,15	1,57	3,18	1,54	2,15	1,81	3,35	3,55
USDMXN 1M_P_10D	2,12	1,16	2,13	1,08	1,27	1,12	2,23	2,00
USDMXN 3M_C_10D	1,97	0,99	1,96	1,12	1,86	1,43	3,50	3,09
USDMXN 3M_P_10D	1,18	0,64	1,18	0,66	0,98	0,74	2,05	2,22
USDMXN 1W_C_25D	4,78	2,15	4,70	2,10	2,42	2,17	3,20	3,08
USDMXN 1W_P_25D	4,10	1,85	4,02	1,92	1,92	1,84	2,32	2,53
USDMXN 2W_C_25D	3,78	1,82	3,80	1,78	1,98	1,83	2,97	2,94
USDMXN 2W_P_25D	3,15	1,52	3,18	1,52	1,64	1,47	2,12	2,77
USDMXN 3W_C_25D	3,23	1,51	3,27	1,67	1,80	1,53	2,97	2,50
USDMXN 3W_P_25D	2,62	1,27	2,62	1,28	1,26	1,21	2,28	2,26
USDMXN 1M_C_25D	2,84	1,34	2,86	1,36	1,53	1,40	2,59	3,40
USDMXN 1M_P_25D	2,24	1,12	2,26	1,11	1,19	1,08	2,18	2,20
USDMXN 3M_C_25D	1,72	0,85	1,72	0,87	1,41	1,10	2,69	3,08
USDMXN 3M_P_25D	1,25	0,67	1,25	0,69	0,89	0,80	2,19	2,25
USDMXN 1W_ATM	4,38	2,02	4,30	1,97	1,97	1,94	2,73	2,63
USDMXN 2W_ATM	3,41	1,61	3,42	1,63	1,66	1,65	2,38	2,58
USDMXN 3W_ATM	2,87	1,31	2,85	1,40	1,69	1,32	2,74	2,57
USDMXN 1M_ATM	2,48	1,17	2,50	1,16	1,25	1,26	2,42	2,88
USDMXN 3M_ATM	1,42	0,74	1,43	0,74	1,10	0,96	2,41	2,49

Table 6.19: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/ZAR under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDZAR 1W_C_10D	3,26	1,71	3,28	1,66	1,81	1,81	3,25	3,32
USDZAR 1W_P_10D	2,59	1,45	2,60	1,20	1,43	1,36	2,78	2,11
USDZAR 2W_C_10D	2,75	1,44	2,75	1,50	1,78	1,58	3,23	3,36
USDZAR 2W_P_10D	2,09	1,22	2,09	1,20	1,42	1,27	2,97	2,82
USDZAR 3W_C_10D	2,30	1,12	2,31	1,14	1,66	1,42	3,69	2,95
USDZAR 3W_P_10D	1,67	0,85	1,67	0,87	1,31	1,13	2,32	2,49
USDZAR 1M_C_10D	2,14	1,04	2,12	1,06	1,58	1,33	3,49	4,95
USDZAR 1M_P_10D	1,50	0,76	1,50	0,82	1,32	1,18	2,66	2,82
USDZAR 3M_C_10D	1,46	0,77	1,48	0,70	1,22	0,89	3,10	3,77
USDZAR 3M_P_10D	0,93	0,45	0,94	0,44	1,46	1,14	2,23	3,00
USDZAR 1W_C_25D	3,03	1,50	3,00	1,52	1,73	1,61	3,26	2,72
USDZAR 1W_P_25D	2,64	1,34	2,63	1,31	1,57	1,36	2,41	2,84
USDZAR 2W_C_25D	2,49	1,30	2,48	1,32	1,50	1,33	3,17	3,21
USDZAR 2W_P_25D	2,11	1,19	2,13	1,19	1,28	1,23	2,31	2,50
USDZAR 3W_C_25D	2,05	0,97	2,04	1,01	1,54	1,16	2,93	3,26
USDZAR 3W_P_25D	1,69	0,83	1,69	0,87	1,34	1,19	2,58	2,98
USDZAR 1M_C_25D	1,87	0,88	1,87	0,94	1,45	1,23	3,32	3,04
USDZAR 1M_P_25D	1,52	0,77	1,51	0,77	1,33	1,03	2,35	2,92
USDZAR 3M_C_25D	1,22	0,60	1,23	0,65	0,99	0,99	2,99	3,49
USDZAR 3M_P_25D	0,94	0,47	0,94	0,45	1,37	1,06	2,39	2,86
USDZAR 1W_ATM	2,78	1,39	2,77	1,37	1,67	1,38	2,52	2,67
USDZAR 2W_ATM	2,24	1,26	2,26	1,27	1,36	1,31	3,39	2,74
USDZAR 3W_ATM	1,81	0,86	1,81	0,91	1,45	1,26	2,76	3,03
USDZAR 1M_ATM	1,64	0,80	1,63	0,80	1,26	1,03	2,45	3,18
USDZAR 3M_ATM	1,02	0,48	1,02	0,48	1,17	0,94	2,80	2,49

Table 6.20: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/ZAR under Rolling-Window Framework*

Targets	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDZAR 1W_C_10D	3,21	1,69	3,16	1,67	1,74	1,70	2,90	3,33
USDZAR 1W_P_10D	2,55	1,42	2,50	1,22	1,41	1,34	2,18	2,41
USDZAR 2W_C_10D	2,71	1,44	2,68	1,50	1,66	1,55	3,19	4,20
USDZAR 2W_P_10D	2,06	1,22	2,06	1,19	1,31	1,18	2,75	3,01
USDZAR 3W_C_10D	2,27	1,13	2,28	1,15	1,50	1,50	3,30	4,26
USDZAR 3W_P_10D	1,64	0,86	1,64	0,83	1,37	1,08	2,78	2,13
USDZAR 1M_C_10D	2,10	1,03	2,09	1,06	1,46	1,21	3,78	3,59
USDZAR 1M_P_10D	1,48	0,76	1,47	0,82	1,31	1,01	3,17	3,05
USDZAR 3M_C_10D	1,44	0,75	1,44	0,70	1,43	0,88	2,63	3,90
USDZAR 3M_P_10D	0,92	0,44	0,92	0,43	1,34	1,27	2,87	3,10
USDZAR 1W_C_25D	2,98	1,52	2,93	1,52	1,60	1,54	3,02	3,27
USDZAR 1W_P_25D	2,60	1,34	2,55	1,30	1,43	1,41	2,66	3,19
USDZAR 2W_C_25D	2,45	1,30	2,42	1,35	1,50	1,41	2,92	3,42
USDZAR 2W_P_25D	2,08	1,18	2,06	1,14	1,33	1,22	2,67	2,97
USDZAR 3W_C_25D	2,01	0,97	2,01	1,03	1,45	1,20	3,34	3,95
USDZAR 3W_P_25D	1,66	0,83	1,65	0,84	1,17	1,19	2,57	2,89
USDZAR 1M_C_25D	1,84	0,89	1,82	0,98	1,33	1,14	3,38	3,83
USDZAR 1M_P_25D	1,50	0,77	1,49	0,76	1,11	0,95	2,49	3,23
USDZAR 3M_C_25D	1,20	0,59	1,19	0,58	1,15	0,83	2,88	3,15
USDZAR 3M_P_25D	0,92	0,47	0,92	0,48	1,26	0,98	2,29	2,70
USDZAR 1W_ATM	2,74	1,40	2,72	1,36	1,48	1,43	2,50	2,87
USDZAR 2W_ATM	2,21	1,24	2,19	1,27	1,23	1,29	2,94	3,15
USDZAR 3W_ATM	1,78	0,86	1,77	0,92	1,27	1,18	2,33	3,39
USDZAR 1M_ATM	1,61	0,80	1,60	0,80	1,21	0,96	2,44	2,95
USDZAR 3M_ATM	1,00	0,48	1,00	0,47	1,30	0,90	2,64	2,66

Table 6.21: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/BRL under Expanding-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDBRL 1W_C_10D	4,59	2,23	4,54	2,22	2,84	2,56	5,42	5,52
USDBRL 1W_P_10D	3,72	1,99	3,68	2,04	2,42	2,20	4,51	4,70
USDBRL 2W_C_10D	3,90	1,84	3,90	1,98	2,38	2,20	4,75	4,42
USDBRL 2W_P_10D	2,78	1,65	2,78	1,66	2,07	1,82	4,11	4,60
USDBRL 3W_C_10D	3,00	1,48	2,98	1,60	2,16	1,79	4,65	5,39
USDBRL 3W_P_10D	2,20	1,29	2,18	1,32	1,81	1,46	4,13	4,39
USDBRL 1M_C_10D	2,71	1,39	2,70	1,37	1,77	1,55	4,77	5,55
USDBRL 1M_P_10D	1,93	1,17	1,93	1,16	1,51	1,33	4,27	4,44
USDBRL 3M_C_10D	1,79	0,88	1,80	1,00	1,98	1,12	4,60	4,77
USDBRL 3M_P_10D	1,22	0,67	1,23	0,73	1,93	1,53	4,98	4,78
USDBRL 1W_C_25D	4,32	2,09	4,25	2,11	2,82	2,66	4,69	4,87
USDBRL 1W_P_25D	3,81	1,99	3,78	2,02	2,68	2,42	4,42	4,57
USDBRL 2W_C_25D	3,51	1,75	3,50	1,85	2,48	2,01	4,55	4,64
USDBRL 2W_P_25D	2,91	1,64	2,91	1,72	2,03	1,90	4,06	4,62
USDBRL 3W_C_25D	2,76	1,39	2,77	1,51	2,09	1,70	4,34	4,45
USDBRL 3W_P_25D	2,25	1,30	2,24	1,33	1,95	1,54	4,51	4,81
USDBRL 1M_C_25D	2,47	1,28	2,45	1,27	2,03	1,37	4,73	5,44
USDBRL 1M_P_25D	1,97	1,14	1,96	1,18	1,95	1,45	4,59	4,92
USDBRL 3M_C_25D	1,59	0,79	1,61	0,84	1,27	1,19	4,08	4,62
USDBRL 3M_P_25D	1,22	0,71	1,24	0,71	2,02	1,65	4,36	4,65
USDBRL 1W_ATM	4,02	2,04	3,96	2,05	2,90	2,35	4,28	4,43
USDBRL 2W_ATM	3,15	1,66	3,15	1,79	2,37	1,93	4,68	4,91
USDBRL 3W_ATM	2,46	1,33	2,48	1,35	2,00	1,50	4,65	4,03
USDBRL 1M_ATM	2,16	1,22	2,15	1,24	1,66	1,46	4,23	4,58
USDBRL 3M_ATM	1,35	0,73	1,36	0,89	2,06	1,18	4,38	4,70

Table 6.22: *Out-of-Sample Five-Day-Ahead RMSE Results for USD/BRL under Rolling-Window Framework*

Targets	**AR**	**PCR**	**PCA-VAR**	**FNN1**	**FNN2**	**FNN3**	**FNN4**	**FNN5**
USDBRL 1W_C_10D	4,52	2,22	4,42	2,26	2,94	2,69	5,07	6,21
USDBRL 1W_P_10D	3,67	1,95	3,59	2,05	2,63	2,48	4,34	4,80
USDBRL 2W_C_10D	3,84	1,87	3,82	2,05	2,79	2,21	5,20	5,42
USDBRL 2W_P_10D	2,74	1,69	2,73	1,68	2,15	1,83	4,25	4,30
USDBRL 3W_C_10D	2,96	1,50	2,94	1,65	2,43	1,82	3,72	4,46
USDBRL 3W_P_10D	2,17	1,35	2,17	1,38	1,66	1,51	4,05	4,24
USDBRL 1M_C_10D	2,68	1,39	2,65	1,38	2,27	1,82	5,51	4,62
USDBRL 1M_P_10D	1,91	1,17	1,91	1,19	1,88	1,31	4,46	3,90
USDBRL 3M_C_10D	1,78	0,88	1,79	0,97	1,48	1,25	3,99	4,00
USDBRL 3M_P_10D	1,21	0,69	1,21	0,76	1,96	1,56	4,05	4,24
USDBRL 1W_C_25D	4,26	2,10	4,17	2,16	2,80	2,65	5,13	4,81
USDBRL 1W_P_25D	3,76	1,98	3,69	2,05	3,24	2,45	4,69	4,95
USDBRL 2W_C_25D	3,46	1,75	3,43	1,92	2,48	1,98	4,77	5,03
USDBRL 2W_P_25D	2,87	1,67	2,84	1,74	2,16	1,90	4,42	5,04
USDBRL 3W_C_25D	2,73	1,41	2,71	1,56	2,07	1,66	4,08	4,17
USDBRL 3W_P_25D	2,23	1,35	2,23	1,34	1,66	1,59	4,11	3,91
USDBRL 1M_C_25D	2,44	1,29	2,42	1,31	1,71	1,58	4,22	4,71
USDBRL 1M_P_25D	1,95	1,15	1,95	1,16	2,21	1,49	4,25	4,57
USDBRL 3M_C_25D	1,58	0,78	1,59	0,82	1,29	1,08	4,35	4,60
USDBRL 3M_P_25D	1,21	0,74	1,22	0,73	1,66	1,39	4,18	4,54
USDBRL 1W_ATM	3,96	2,00	3,90	2,07	2,73	2,47	4,38	4,95
USDBRL 2W_ATM	3,10	1,69	3,07	1,82	2,54	1,89	3,98	4,19
USDBRL 3W_ATM	2,43	1,34	2,42	1,41	1,62	1,54	4,40	4,54
USDBRL 1M_ATM	2,14	1,22	2,14	1,22	1,80	1,53	4,64	4,04
USDBRL 3M_ATM	1,34	0,72	1,34	0,91	1,65	1,22	4,22	4,20

Table 6.23: *Out-of-Sample One-Day-Ahead RMSE Performance Using Expanding Window Approach Across Currencies*

Currencies	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDTRY	2,71	2,96	2,72	3,00	5,14	3,68	10,67	11,50
USDINR	0,56	0,29	0,55	0,29	0,55	0,39	0,93	0,89
USDMXN	1,55	0,59	1,56	0,60	1,11	0,88	2,54	2,55
USDZAR	1,16	0,54	1,15	0,53	1,18	1,04	2,96	3,07
USDBRL	1,42	0,72	1,42	0,74	1,68	1,32	4,42	4,65

Table 6.24: *Out-of-Sample One-Day-Ahead RMSE Performance Using Rolling Window Approach Across Currencies*

Currencies	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDTRY	2,66	2,96	2,64	3,08	6,26	4,09	11,03	11,95
USDINR	0,56	0,29	0,53	0,29	0,54	0,41	0,93	0,92
USDMXN	1,53	0,60	1,52	0,60	1,14	0,89	2,55	2,71
USDZAR	1,15	0,55	1,13	0,54	1,15	0,95	3,03	3,20
USDBRL	1,40	0,73	1,39	0,74	1,76	1,32	4,54	4,75

Table 6.25: *Out-of-Sample Five-Day-Ahead RMSE Performance Using Expanding Window Approach Across Currencies*

Currencies	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDTRY	4,25	6,96	4,25	7,33	8,11	7,06	11,56	13,10
USDINR	1,03	0,61	1,02	0,67	0,71	0,63	1,03	1,01
USDMXN	3,05	1,44	3,08	1,47	1,63	1,50	2,69	2,70
USDZAR	1,99	1,22	1,99	1,02	1,44	1,25	2,85	3,02
USDBRL	2,71	1,43	2,70	1,48	2,13	1,75	4,51	4,75

Table 6.26: *Out-of-Sample Five-Day-Ahead RMSE Performance Using Rolling Window Approach Across Currencies*

Currencies	AR	PCR	PCA-VAR	FNN1	FNN2	FNN3	FNN4	FNN5
USDTRY	4,17	6,94	4,15	7,93	7,89	7,04	12,36	11,74
USDINR	1,01	0,61	0,99	0,66	0,72	0,64	1,02	1,02
USDMXN	3,00	1,44	2,99	1,45	1,67	1,50	2,65	2,73
USDZAR	1,96	1,02	1,94	1,02	1,37	1,21	2,82	3,22
USDBRL	2,68	1,44	2,65	1,50	2,15	1,80	4,42	4,58