MALAYSIAN JOURNAL OF SCIENCE
MJS
ISSN 1394-3065

Regular Issue

Malaysian Journal of Science 44 (3): 64-72 (September 2025) https://mjs.um.edu.my

The Effects of Technical Indicators on Exchange Rates: Empirical Insights from Quantile Regression Models

Basnayake B.R.P.M.[1ab] and Chandrasekara N.V.[2a]

Abstract: The modelling and forecasting of foreign exchange rates have proven challenging due to the prevailing extreme volatility and uncertain nature. Therefore, the primary objective of this investigation is to analyze and model the dynamics of exchange rates of the EURO, GBP, and USD against LKR using technical indicators of the previous day's low, high, and opening price, along with lagged and moving average (MA) values of closing prices. The generalized lambda distribution (GLD) regression models were employed in this study due to the non-normal behaviour exhibited by the error term. The GLD, being a versatile probability distribution, can encompass diverse distributional forms. Regarding the fitted GLD regression models, quantile regression (QR) models were utilised under two distinct conditions on closing price values of exchange rates: Case-I, coefficients were permitted to vary while maintaining a fixed intercept; Case-II, all coefficients were allowed to vary. The empirical study uses the daily data collected from the Yahoo Finance website from January 1, 2008, to February 28, 2022. Our findings show that the influence of technical indicators on exchange rate returns varies significantly across different quantiles. The models that demonstrated superior performance fall under Case-I, and based on the lower quantile of 0.1, for EURO/LKR with a mean absolute error (MAE) of 1.3246 and mean absolute percentage error (MAPE) of 0.0058, and for GBP/LKR with the minimum errors of MAE of 1.2253 and MAPE of 0.0045. For USD/LKR, the QR model fitted with the 0.5 quantile demonstrated the lowest errors with MAE of 1.1369 and MAPE of 0.0057. These findings hold significance as forecasts of exchange rates play an important role in financial decision-making processes.

Keywords: *Exchange rate, generalized lambda distribution (GLD), GLD regression, quantile regression, technical indicators*

1. Introduction

The foreign exchange market is the largest and most liquid among financial markets, whereas foreign exchange rates rank as the most important economic indicators in the international monetary arena. Predicting these rates presents numerous theoretical and empirical challenges. Several formal models have emerged in recent years concerning modelling and forecasting time-varying data. Among them, statistical regression models hold a significant role in statistical applications. Many regression models employed in practical contexts are based on a single-fitted line (Su, 2015, 2016; Tsai, 2012). However, quantile regression (QR) is a methodology used to derive multiple regression curves at different quantiles for a given data set, and as a result, users can obtain more comprehensive insights about data (Huang et al., 2011; Kleopatra, 2008; Su, 2016; Tsai, 2012). In ordinary least squares regression, the primary emphasis is usually directed towards estimating the conditional mean of a dependent variable in relation to one or more explanatory variables.

However, QR allows for a complete description of the conditional distribution of exchange rates across various quantiles, whereas the QR estimators provide insights into various points along the conditional distribution by evaluating the effect of explanatory variables on exchange rates (Huang et al., 2011; Kleopatra, 2008; Su, 2016; Tsai, 2012). The QR focuses not only on the mean effect but also on the entire distribution of exchange rates. Furthermore, the QR estimator resists outlier observations in the dependent variable and can perform efficiently when the error term departs from normality. The GLDs represent quantile functions that exhibit the capacity to effectively model a wide range of empirical data, as it is a versatile distribution with the ability to represent multiple distribution shapes (Su, 2015). Hence, QR based on GLD stands as a resilient and versatile alternative when compared with the conventional standard QR models, as the reference line is resistant to the outliers and QR models can be obtained with smooth regression coefficients based on the reference GLD regression model for specified quantiles (Su, 2015).

Furthermore, QR based on GLD not only addresses the limitations of traditional QR models but also enhances the flexibility in capturing different distributional shapes, such as skewness and kurtosis, within the data. The GLD framework allows for a more precise fit across various quantiles, making it particularly effective when exchange rate movements exhibit non-normal characteristics, such as heavy tails or asymmetry. This approach also improves the precision of forecasting models by adjusting for the heterogeneity in the data across different quantiles, thus providing a better understanding of the exchange

Authors information:
[a]Department of Statistics & Computer Science, University of Kelaniya, Kelaniya, SRI LANKA. E-mail: pavithrab@sci.pdn.ac.lk[1]; nvchandrasekara@kln.ac.lk[2]
[b]Department of Statistics & Computer Science, University of Peradeniya, Peradeniya, SRI LANKA. E-mail: pavithrab@sci.pdn.ac.lk[1]
*Corresponding Author: pavithrab@sci.pdn.ac.lk

Received: January, 2024
Accepted: October, 2024
Published: September, 2025

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

rate dynamics. It is essential to analyze the recent historical behaviour of these currency exchange rates to forecast future trends (Huang et al., 2011; Kleopatra, 2008). However, a country's exchange rate is correlated with factors such as money supply, output, interest rates, and inflation. In this study, the omission of these factors arises, as macroeconomic variables are primarily accessible on a monthly basis. Nevertheless, within the finance domain, it becomes necessary to address high-frequency data occurring daily or hourly. Hence, to avoid these challenges, this investigation considered technical indicators and the distribution of the error term in modelling the behaviour of the exchange rates. The main aim of this study is to identify the impact of technical indicators of the previous day's close, low, high, and opening prices, along with the MA of the close price on the movements of exchange rates.

This empirical study is the first approach that employed GLD-based QR models to obtain a comprehensive description of the conditional distribution of exchange rates across lower, central, and upper quantiles. The subsequent aim of this study is to identify how the effects of technical indicators vary across different quantiles of the exchange rate movements. Traditional mean-based regression models often overlook the heterogeneous impacts these indicators can have on different data segments. Understanding these variations is crucial for providing more thorough ideas on exchange rate dynamics. Such insights will enhance forecasting models' accuracy and support investment and policy decisions.

In this study, the authors contribute to the literature by applying the QR model based on generalized lambda distribution (GLD) to predict the exchange rate between the Euro (EURO), United States dollar (USD), and British pound sterling (GBP) against the Sri Lankan Rupee (LKR). Technical indicators of the preceding day's low, high, and open price values, along with the lags of close price (observed values from the previous days), moving average (MA) of one week (MA7), two weeks (MA14), one month (MA28), three-month period (MA84), and six-month period (MA168), are used as inputs to develop the QR models. In general, it is important to forecast exchange rate movement behaviours accurately, as inappropriate exchange rate policies can impose a negative influence on exports, imports, investments, and economic growth. Hence, this investigation employs QR models to model the fluctuations in exchange rates.

The objective of understanding the heterogeneous effects of technical indicators on exchange rates is well-supported by existing literature emphasizing the complexity and importance of exchange rate dynamics. However, only a limited number of studies have applied the QR model to explore exchange rate dynamics. For instance, a researcher proposed that QR models possess the ability to capture the effects of historical data on the real exchange rate, and he mentioned that the QR models can assist in the identification of dynamic and asymmetric behaviours within the data (Kleopatra, 2008). The findings indicate that larger shocks led to mean-reverting behaviour in the exchange rate at the extreme quantiles. The mean reversion accelerates when large shocks occur at substantial real exchange rate deviations from the long-term equilibrium. Conversely, in the absence of such shocks, mean reversions were not observed. In another study, authors argued that the QR methodology provides exchange rate volatility forecasts with higher accuracy when compared to alternative prominent techniques (Huang et al., 2011). They employed several statistical techniques, including moving average, Monte Carlo simulation, generalized autoregressive conditional heteroscedasticity (GARCH), interval regression, interval approximation, and QR to model and forecast nine daily real exchange rates based on nominal exchange rate values and consumer price indices.

This work advanced the use of the conditional autoregressive value at risk by the regression quantiles model for volatility forecasting by establishing a structured regression relationship between volatility and a uniformly distributed series of quantiles. Instead of focusing solely on tail quantiles, a series of percentiles generated by this model was employed to explain volatility dynamics. Further, the QR model was applied in a different scholarly investigation to explore the correlation between the stock price index and exchange rates within Asian markets (Tsai, 2012). Due to the assumptions violated by traditional ordinary least squares estimation, a quantile regression model is employed, and this investigation concluded that there is an inverse relationship between the variables when exchange rate values were at exceptionally high or low levels. Another study utilized QR models to analyze the impact of fluctuations in the supply and demand of the oil market on currency exchange rates (Su, 2016). Their findings revealed that the impact of oil shocks on exchange rates varies significantly across distinct quantiles. The coefficients estimated for the oil shock variables at both the lower and upper quantiles indicated that USD depreciation or appreciation intensified the reactions of exchange rates to oil shocks.

Recent research applied a combination of multiple linear regression (MLR), QR models, and k-nearest neighbour models to examine the daily variations in the exchange rate dynamics between the USD and the Chinese Yuan using the variables of the daily count of confirmed cases of new coronavirus pneumonia, the daily deaths of each day, the daily number of recovered cases, and the prevailing interest rate (Zhang et al., 2021). Some of the notable findings of their study were that at the 0.5 quantile, a daily increment of one unit in newly diagnosed cases correlated with a corresponding decrease of 0.00001% in the exchange rate. At the 0.75 quantile, a daily increment of one unit in newly cured cases was associated with a consequential change in the exchange rate, amounting to -0.00003%.

Nevertheless, there has been no comprehensive examination of the heterogeneous effects of technical indicators on exchange rates within the framework of the QR model in the referred literature. Further, Sri Lanka is presently facing significant economic difficulties due to the depreciation of the LKR. This depreciation has caused a widening trade deficit and increased inflation, which are adversely influencing domestic and international investors' decisions. Nevertheless, these negative effects can be identified early through thorough modelling and

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

forecasting of exchange rate movements. Hence, this study offers a valuable contribution by applying advanced QR modelling techniques, which improve the accuracy of forecasting exchange rate movements and provide policymakers and investors with timely insights to mitigate the adverse effects of currency depreciation and economic instability.

The subsequent sections of this paper are structured as follows: The Methodology section outlines the methods employed in the analysis. The empirical findings section presents the data and their corresponding descriptive statistics along with the main findings from the fitted models. The Conclusion section provides the conclusion of this study.

2. Methodology

Daily data from January 1, 2008, to February 28, 2022, for EURO/LKR, GBP/LKR, and USD/LKR were sourced from the Yahoo Finance website for this study. The data from January 1, 2008, to January 7, 2022, was used for model training, while the remaining dataset was used to test the fitted models. The daily closing price of exchange rates was modelled by the technical indicators of the previous day's low, high, and opening price data, as well as lags in the closing price as observed in the autocorrelation function (ACF) plot and using the MA values for periods of one week (MA7), two weeks (MA14), one month (MA28), one quarter (MA84), and six months (MA168), which respectively represent the moving average trends over these timeframes. Here, the opening price refers to the market price at the beginning of the period. The high price and the low price represent the highest and the lowest market prices observed during the period, where the closing price signifies the market price at the end of the period. It is important to ascertain the stationarity of the dataset prior to the analysis when handling time series data. This study initially conducted unit root tests (Augmented Dickey-Fuller test (ADF), Phillips-Perron test (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests) to address the issue of spurious regression. The non-stationary time series was transformed into a stationary one by applying the first difference technique.

Initially, MLR models were fitted to assess whether these models have the ability to accurately capture the patterns in the exchange rate data, while satisfying model assumptions. More details of the methodology employed for fitting the MLR model and assessing its underlying assumptions can be found in the work of Rodríguez & Benítez-Parejo (Rodríguez & Benítez-Parejo, 2011). Nonetheless, owing to the violation of model assumptions in MLR models, the GLD regression model was applied.

GLD Distribution

The Freimer-Mudholkar-Kollia-Lin GLD (FMKL GLD) (Freimer et al., 1988) is defined by its inverse distribution function as Eq. (1):

$$F^{-}(u;\, \lambda_1, \lambda_2, \lambda_3, \lambda_4) = \lambda_1 + \frac{1}{\lambda_2}\left(\frac{u^{\lambda_3}-1}{\lambda_3} - \frac{(1-u)^{\lambda_4}-1}{\lambda_4}\right), \quad 0 \le u \le 1 \qquad (1)$$

where λ_1 is the location parameter, λ_2 is the scale parameter ($\lambda_2 > 0$), and λ_3 and λ_4 are shape parameters of skewness and kurtosis, respectively. For the existence of a finite kth moment, $min(\lambda_3, \lambda_4) > \frac{-1}{k}$. A comprehensive analysis regarding the forms and characteristics of GLD distribution is available within the original published paper (Freimer et al., 1988).

GLD Regression Model

The methodology for GLD regression models was introduced by Su (2015). To find the regression coefficients of the GLD regression model in Eq. (2), the least squares method is applied.

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i1} + \hat{\beta}_2 x_{i2} + \cdots + \hat{\beta}_k x_{ik} \qquad (2)$$

where y_i is the actual value of the dependent variable at the ith observation, $\hat{y}_i$ is the estimated value at the i^{th} observation, $\hat{\varepsilon}_i = y_i - \hat{y}_i$ and $i = 1,2,3,\dots,n$, $\hat{\beta}_k$ represents the estimated regression coefficient of k^{th} explanatory variable and $j = 1,2,3,\dots,k$ and x_{ik} is the value of i^{th} observation the k^{th} explanatory variable.

The coefficients of β are computed considering the condition of error terms, $\varepsilon \sim GLD(\lambda_1, \lambda_2, \lambda_3, \lambda_4)$ where $E(\varepsilon) = 0$ and ε are modelled using maximum likelihood estimation (Su, 2015, 2016). Here, the zero-mean residual line is obtained by allowing the parameters λ_2, λ_3 and $\lambda_4$vary in the process of optimization, while simultaneously adjusting the intercept of the line such that the summation of error terms is equal to zero. The Nelder-Mead simplex algorithm is used to determine the maximum value of the log-likelihood, as this algorithm stands as the most stable approach for tasks of optimizing and estimating associated with GLD. Statistical characteristics of the regression coefficients in the GLD model are ascertained through the replication of real observations $y_i = \hat{y}_i + \hat{\varepsilon}_i$ for $i = 1, 2, 3, \dots, n$ by simulating $\hat{\varepsilon}_i \sim GLD(\hat{\lambda}_1, \hat{\lambda}_2 \hat{\lambda}_3, \hat{\lambda}_4)$ and the subsequent re-estimation of the complete model. The maximum likelihood estimation was used to determine a robust GLD regression line, as this estimation considers that outliers are relatively negligible in shaping the overall distribution. The Cramer-Von Mises (CvM) and Anderson-Darling (AD) tests were employed to assess the conformity of residuals with GLD in the fitted GLD QR models.

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

GLD-based QR Model

When a reference GLD regression line is fitted, the QR can be obtained by Case-I, fixing the intercept, or Case-II, allowing all coefficients to vary for heteroscedastic data using the Nelder-Mead simplex algorithm (Su, 2015, 2016). To parametrically calculate the coefficients of the QR model concerning the GLD regression line, the Nelder-Mead simplex algorithm is used to solve Eq. (3).

$$\min(F_{GLD}(\hat{\lambda}_1^{\alpha}, \hat{\lambda}_2^{\alpha}, \hat{\lambda}_3^{\alpha}, \hat{\lambda}_4^{\alpha}) - \alpha)^2 \quad i = 1,2,3, \dots, n \qquad 0 \leq \alpha \leq 1 \tag{3}$$

where $F_{GLD}(0, \hat{\lambda}_1^{\alpha}, \hat{\lambda}_2^{\alpha}, \hat{\lambda}_3^{\alpha}, \hat{\lambda}_4^{\alpha})$ is the cumulative FKML GLD density function fitted to error terms $\hat{\varepsilon}_i^{\alpha} = y_i - (\hat{\beta}_0^{\alpha} + \hat{\beta}_1^{\alpha} x_{i1} + \hat{\beta}_2^{\alpha} x_{i2} + \dots + \hat{\beta}_k^{\alpha} x_{ik})$ at the quantile of α.

In Case-I, the parameter estimate $\hat{\beta}_0^{\alpha}$ remains fixed throughout the optimization process, while the remaining coefficients are permitted to vary, and in Case-II, all coefficients are allowed to vary. For instance, to find the QR line at the lower quantile of α = 0.1, the quantile line needs to possess the characteristic that 10% of the observations lie below it. This objective can be realized by identifying a line that fulfills the specified criteria of $F_{GLD}(\hat{\lambda}_1^{0.1}, \hat{\lambda}_2^{0.1}, \hat{\lambda}_3^{0.1}, \hat{\lambda}_4^{0.1}) = 0.1$.

The pseudo R^2 is used as a metric to assess the capacity of independent variables in explaining the variation of close value of exchange rates in QR models. In the final stages of the analysis, insignificant variables were removed from the GLD-based QR model to improve its predictive accuracy and reliability. The initial model included a comprehensive set of technical indicators, such as the previous day's close, low, high, and opening prices, as well as the MA of the close price. However, during the model estimation process, some variables were found to have statistically insignificant impacts on the exchange rate movements across the quantiles. These insignificant variables were systematically excluded based on their p-values and contribution to the model's explanatory power. The model was then refitted without these variables, ensuring that only those indicators with meaningful effects remained. Here, insignificant variables were removed, and the models were refitted. In assessing forecast accuracy, all fitted models were evaluated using metrics such as mean absolute error (MAE) and mean absolute percentage error (MAPE). This study used lower quantiles of 0.01, 0.05, 0.10, and the median quantile (0.50) and upper quantiles of 0.90, 0.95, 0.99 to fit the QR models to exchange rates.

3. Empirical Findings

Figure 1 illustrates the behaviour of EURO/LKR, GBP/LKR, and USD/LKR over time. Since the beginning of 2008, exchange rates have fluctuated, and upward trends have been observable since 2019. The highest exchange rate values of 240.854 and 278.336 occurred on May 26, 2021, for EURO/LKR and GBP/LKR, respectively, while the USD/LKR exchange rate reached its maximum value of 200.292 on December 20, 2021.

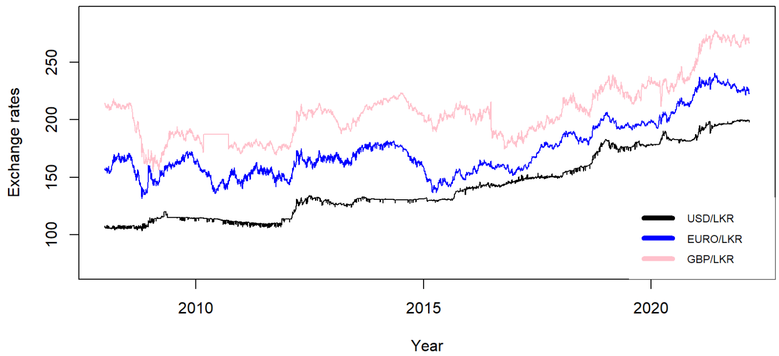

Figure 1. Behaviour of exchange rates over time.

The summary statistics of the three exchange rates considered are presented in Table 1. All standard deviations (SDs) lie between 24 and 29, and all the variables are positively skewed. The positive excess kurtosis values observed in EURO/LKR and GBP/LKR indicate a leptokurtic distribution, characterized by sharply peaked behaviour and heavy tails. In contrast, the negative excess kurtosis values of USD/LKR signify a platykurtic distribution, featuring a flat peak and lighter tails. The ADF, PP, and KPSS test results observed the presence of a unit root in each variable. The non-stationary data were transformed into stationary data by employing the first difference technique. Initially, MLR models were applied to capture the movements of the exchange rates. Multicollinearity was detected in fitted MLR models for USD/LKR and GBP/LKR as VIF values were greater than 10. The issue of multicollinearity was addressed by removing the independent variable. The p-values obtained from the Durbin-Watson test exceeded 0.05, indicating the absence of autocorrelations in the residuals at a 5% significance level in each fitted MLR model (Rodríguez & Benítez-Parejo, 2011). However, all the models exhibited residuals with non-normal distributions and

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

heteroscedasticity (p-values below 0.05) by CvM, AD tests, and Breusch-Pagan test, respectively.

The GLD serves as a quantile function that demonstrates a flexible capacity in modelling diverse empirical data, owing to its ability to accommodate various distribution shapes. Consequently, the regression model based on GLD emerges as a reliable and versatile alternative to the conventional regression model, as discussed in the Introduction and Methodology sections. Hence, GLD regression was employed, as detailed in Eq. (4) to Eq. (6).

Table 1. Summary statistics of the considered three exchange rates.

	USD/LKR				EURO/LKR				GBP/LKR			
	Low	High	Open	Close	Low	High	Open	Close	Low	High	Open	Close
Minimum	102.8800	105.9600	102.8800	103.3600	131.3930	135.2400	131.3930	131.3930	153.6500	156.9400	154.1800	155.0600
Maximum	199.8290	200.6712	200.6712	200.2916	239.4303	240.8536	240.8536	240.8536	277.3640	278.3357	278.3293	278.3357
Mean	141.0841	142.2435	141.2622	141.6284	173.3498	174.6483	173.8308	173.8425	206.4488	208.3618	207.0670	207.4923
SD	28.0903	28.2991	28.0880	28.3626	25.0581	24.6852	24.9814	24.9836	25.8862	25.6902	25.6704	25.8773
Skewness	0.6032	0.5767	0.6042	0.5884	0.9214	0.9341	0.9201	0.9242	0.8478	0.8072	0.8690	0.8214
Excess Kurtosis	-0.8420	-0.9324	-0.8344	-0.8974	0.0002	0.0418	0.0078	0.0172	0.5352	0.4511	0.5870	0.4517
ADF test	0.7705	0.7185	0.7666	0.6845	0.6154	0.6306	0.5941	0.5881	0.4632	0.4091	0.4393	0.4343
PP test	0.5756	0.7219	0.5349	0.5359	0.6068	0.6436	0.5712	0.5738	0.4209	0.3361	0.3874	0.3462
KPSS test	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100	0.0100

$$Y_{EURO} = 0.0002 + 0.9974 * Open + 0.0005 * High + 0.0004 * Low + 0.0019 * Lag\ 1 + 0.0045 * Lag\ 2 + 0.0033 * Lag\ 3 + 0.0011 * Lag\ 6 + 0.0090 * Lag\ 7 + 0.0069 * Lag\ 8 + 0.0039 * MA7 - 0.0072 * MA14 + 0.0273 * MA28 - 0.0805 * MA84 + 0.0121 * MA168$$
where $\lambda_1 = 0.0001,\ \lambda_2 = 23.7736,\ \lambda_3 = -0.6683,\ \lambda_4 = -0.6680.$ (4)

$$Y_{USD} = 0.0078 + 0.2266 * High + 0.01035 * Low - 0.0116 * Lag\ 1 - 0.0057 * Lag\ 3 + 0.0059 * Lag\ 6 - 0.0010 * Lag\ 7 + 0.0040 * Lag\ 8 - 0.0107 * MA7 + 0.0829 * MA14 - 0.0462 * MA28 - 0.3399 * MA84 + 0.6018 * MA168$$
where $\lambda_1 = -0.0095,\ \lambda_2 = 21.4539,\ \lambda_3 = -0.9552,\ \lambda_4 = -0.9556.$ (5)

$$Y_{GBP} = 0.0013 - 0.0005 * High + 0.7138 * Low - 0.0423 * Lag\ 1 - 0.0402 * Lag\ 3 + 0.0035 * Lag\ 6 + 0.1908 * MA7 - 0.0083 * MA14 - 0.0725 * MA28 + 0.1615 * MA84 - 0.0328 * MA168$$
where $\lambda_1 = 0.0031,\ \lambda_2 = 5.6036,\ \lambda_3 = -0.4951,\ \lambda_4 = -0.4906.$ (6)

For the aforementioned models, the results of the CvM and AD tests revealed that the residuals conform to GLDs with p-values exceeding 0.05, thus demonstrating statistical significance at the 5% level. As the reference GLD regression lines are fitted, QR models were employed in two cases due to heteroscedasticity in the residuals. In Case-I, coefficients were allowed to vary while maintaining a fixed intercept. In Case-II, all coefficients were allowed to vary. This study will involve estimating QR for lower quantiles (0.01, 0.05, and 0.1), the central quantile (0.5), and upper quantiles (0.90, 0.95, and 0.99). From Tables 2 to 4, a comprehensive analysis is presented for Case-I to outline the general effects of technical indicators on the closing values of exchange rates for EURO/LKR, GBP/LKR, and USD/LKR.

This analysis has yielded several interesting findings. Overall, the open values exhibit no statistically significant effect on the closing values of the exchange rates. In accordance with the information presented in Table 2, under Case-I for EURO/LKR, the High variable demonstrates a positive influence at lower and upper quantiles. In comparison, the Low variable exhibits a positive impact on lower quantiles and a negative influence on central and upper quantiles. Lag values or historical data from the preceding days exhibited both positive and negative significant effects, without any consistent pattern, except for the absence of a significant impact from Lag 2 (value observed 2 days before) at the central quantile. Additionally, MAs show significant positive and negative effects, except for MA 168 in the upper quantiles, which is not statistically significant. The Pseudo R^2 values associated with QR models are notably low, with the highest value of 0.3747 observed at the central quantile.

According to the results of Table 3, in Case-I for GBP/LKR, the High variable demonstrates a negative influence at lower quantiles except for the 0.1 quantile, which shows no significant effect for the close values and a positive effect at the central quantile. The Low variable is not significant in any quantile. Lag 1 (value observed 1 day before) showed a significant negative effect at each quantile, except it is positive at the 0.05 quantile. Lag 3 (value observed 3 days before) has a significantly negative effect at lower quantiles and in the central quantile and a positive effect at the upper quantiles. Lag 6 (value observed 6 days before) is not significant in lower quantiles, but significant in the central quantile with a positive effect and negative in upper quantiles. MA7 has a significant negative effect at the upper quantiles, and

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

MA28 has a negative effect at all the quantiles except the 0.99 quantile. MA 84 is not significant in any quantile, and MA 168 is significant at some of the lower and upper quantiles, including the central quantile, without any clear pattern. Pseudo R2 values presented in Table 3 indicate that the values within the lower and central quantiles are considerably higher than those within the upper quantiles.

Table 2. Parameter estimates of QR models – Case-I - EURO/LKR.

	α = 0.01	α = 0.05	α = 0.1	α = 0.5	α = 0.9	α = 0.95	α = 0.99
Intercept	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*	0.0002*
Open	0.9875	0.985	0.9975	0.9954	1.0129	1.0206	1.0247
High	0.0224*	0.0306*	0.0083*	0.0515	0.0103*	0.0125*	0.0124*
Low	0.0062*	0.0043*	0.0017*	-0.0010*	-0.0167*	-0.0181*	-0.0164*
Lag 1	0.0005*	-0.0017*	0.0024*	0.0494*	0.0038*	-0.0039*	0.0002*
Lag 2	0.0003*	0.0004*	-0.0005*	0.0543	-0.0030*	-0.0022*	-0.0021*
Lag 3	0.0009*	-0.0014*	-0.0025*	0.0245*	-0.0022*	-0.0019*	-0.0011*
Lag 6	0.0021*	0.0039*	0.0019*	0.0314*	-0.0045*	-0.0057*	-0.0043*
Lag 7	0.0005*	-0.0006*	0.0049*	-0.0436*	-0.0054*	-0.0012*	0.0017*
Lag 8	0.0006*	0.0005*	0.0012*	0.0309*	-0.0003*	0.0004*	0.0000*
MA 7	-0.0026*	0.0017*	0.0002*	0.0498*	0.0077*	-0.0052*	0.0080*
MA 14	-0.0091*	-0.0160*	-0.0067*	0.0065*	0.0143*	0.0277*	-0.0093*
MA 28	0.0085*	0.0383*	0.0167*	0.0287*	0.0093*	0.0074*	0.0348*
MA 84	-0.0193*	-0.0702*	-0.0855*	-0.0925*	-0.0096*	-0.0335*	0.0121*
MA 168	-0.0708*	-0.0605*	-0.0307*	-0.0301*	0.2677	0.3346	0.1798
Pseudo R^2	0.0539	0.091	0.1461	0.3749	0.2026	0.1526	0.1129

* represent the coefficient significant at a 5% level.

Similarly, under Case-I for USD/LKR, the high variable was insignificant at any quantile. In contrast, the low variable was significantly positive and negative at the upper quantiles, including the 0.1 quantile. Here, the lag values showed positive and negative significant and insignificant effects, without any consistent pattern. MA 7 and MA 84 were significant at each quantile, but not MA 14 and MA 168. The MA 28 parameter was not significant at the upper quantiles of 0.95 and 0.99; it was negatively significant at the lower quantiles and positively significant at the central quantile and at the 0.9 quantile. The Pseudo R^2 values exhibited an increase in the lower and central quantiles compared to the upper quantiles.

A similar procedure was executed to fit the QR models under Case-II. However, most variables are not statistically significant at a 5% level of significance in Case-II. For instance, under Case-II in EURO/LKR, the high variable demonstrates a positive and a negative influence at the quantiles of 0.5 and 0.9, respectively. The low variable exhibits a negative impact on the upper quantiles and a positive impact on the central quantile. All the lag values show no significant effects at the lower quantiles of 0.01 and 0.05. However, all lags are significant at the central quantile. In general, most lags are significant at the upper quantiles compared to the lower quantiles. The MA7 parameter is positively significant at the central quantile and negatively significant at the upper quantiles. MA 14 is only significant at the central quantile, and MA 28 is negatively significant at the lower quantile of 0.01 and the upper quantile of 0.99. MA 84 is negatively significant at the central and upper quantiles. MA 168 has significant positive and negative effects at each quantile. The Pseudo R^2 values exhibit lower values across all quantiles, except for the upper quantiles of 0.95 and 0.99.

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

Table 3. Parameter estimates of QR models – Case-I - GBP/LKR.

	α = 0.01	α = 0.05	α = 0.1	α = 0.5	α = 0.9	α = 0.95	α = 0.99
Intercept	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*	0.0013*
High	-0.3950*	-0.3507*	0.0702	0.0434*	0.0827	0.1494	0.0820
Low	0.3723	0.4559	0.7168	0.7431	0.7954	0.7719	0.7839
Lag 1	-0.5378*	0.0283*	-0.0092*	-0.0271*	-0.0266*	-0.0048*	-0.0373*
Lag 3	-0.0142*	-0.1748*	-0.0537*	-0.0348*	0.0180*	0.0245*	0.0120*
Lag 6	0.2524	0.1879	0.0847	0.0174*	-0.0386*	-0.0341*	-0.0377*
MA 7	0.2102	0.1400	0.1594	0.2146	-0.0164*	-0.1222*	-0.0311*
MA 14	0.1032	0.0006*	-0.0395*	0.0154*	0.0951	0.1812	-0.0307*
MA 28	-0.1411*	-0.0617*	-0.0801*	-0.1028*	-0.0340*	-0.0188*	0.0330*
MA 84	0.3215	0.1951	0.1379	0.1602	0.2161	0.1546	0.2089
MA 168	-0.1409*	0.2636	-0.0571*	0.0007*	0.0465*	0.0524	0.0612
Pseudo R^2	0.9958	0.9926	0.9255	0.7151	0.2042	0.1066	0.0429

The empirical findings indicate that parameter estimates differ across quantiles. Moreover, the magnitude and direction of coefficients vary across different quantiles (Su et al., 2016). As shown in Table 1, it is evident that all the exchange rates exhibit skewness and conform to non-normal distributions. This observation suggests that the QR outcomes are more robust than the OLS estimation. The models were refitted after removing the insignificant variables, and these models were used in forecasting. Figure 2 illustrates the performance of all the fitted QR models in Case-I concerning EURO/LKR across various quantiles, compared to the observed empirical behaviour. In a broad sense, these fitted models successfully capture the actual behaviour of the test dataset. Initially, all fitted model values closely approximate the test set values. Nonetheless, by mid-January, the forecasted values from the upper quantiles begin to diverge from the actual data.

Conversely, the lower quantiles and the central quantile consistently replicate the behaviour of the test set, maintaining their accuracy until almost mid-February. Similarly, graphs representing actual and forecasted data were drawn to assess whether the QR models accurately captured the movements of other exchange rates in both Cases. In the context of Case-I, the QR models fitted at the lower quantiles captured the fluctuations in USD/LKR until mid-February 2022. Subsequently, the QR model based on the central quantile began to align closely with the actual values of USD/LKR. For GBP/LKR, each QR model accurately captured the movements up to early February 2022, except for the model corresponding to the 0.05th quantile. In the subsequent period, QR models fitted to lower quantiles of 0.01 and 0.1 effectively capture the behaviour of GBP/LKR. Although actual and fitted lines do not overlap in the later parts, the QR models developed under Case-I successfully captured the patterns in the considered exchange rates.

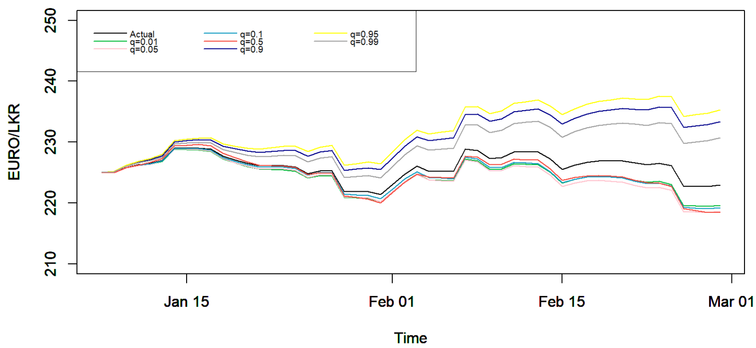

Figure 2. Performance of QR models in Case-I - EURO/LKR.

In Case-I, QR models employing a lower quantile of 0.1 exhibited the lowest error values for EURO/LKR (MAE of 1.3246 and MAPE of 0.0058) and GBP/LKR (MAE of 1.2253 and MAPE of 0.0045), while for USD/LKR, the minimum errors, MAE of 1.1369 and MAPE of 0.0057, were observed in the QR model fitted with the central quantile. Further, Lewis (1982) introduced criteria for categorizing the performance of fitted models based on MAPE. He mentioned that a MAPE below 0.1 indicates highly accurate forecasting, and the MAPE values resulting from this study indicate a high precision level in the fitted models' forecasting capability. Additionally, compared to MAE and MAPE values obtained from SARIMA models fitted in our prior investigation, this study demonstrates better-performing models characterized by reduced error values (Basnayake & Chandrasekara, 2022).

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)

For EURO/LKR, the SARIMA model with a seasonal period of 7 combined with GARCH(1,2) in a skew-normal distribution with a skewness parameter of 0.9843 yielded MAE of 1.8080 and MAPE of 0.0080. For GBP/LKR, the SARIMA model with a seasonal period of 7, combined with ARCH(1) in a skew-t distribution with a skewness parameter of 1.0229 and a shape parameter of 2.0100, resulted in an MAE of 2.9896 and an MAPE of 0.0111. For USD/LKR, the SARIMA model with a seasonal period of 7, combined with GARCH(1,3) in a skew-normal distribution with a skewness parameter of 0.7836, produced an MAE of 2.2751 and an MAPE of 0.0114. These comparative results illustrate the superior performance of the QR models employed in the current analysis.

4. Conclusion

The uncertainty movements in exchange rates have been shown to significantly impact various macroeconomic conditions, including international trade and monetary shocks. Accurate forecasting of exchange rate volatility allows governments and central banks to operate more efficiently in exchange markets and helps reduce hedging costs for firms. Overall, the primary contribution of this study is the comprehensive investigation of the heterogeneous effects of technical indicators on exchange rates within the framework of the GLD-based QR models. This area has not been thoroughly examined in the existing literature. By examining the differential impacts of the previous day's close, low, high, and opening prices, along with the MA of the close price, across various quantiles of the exchange rate distribution, this research provides a more detailed understanding of exchange rate behaviour. By highlighting these heterogeneous effects, the study contributes to the methodological advancement of exchange rate modelling and offers practical implications for economic and investment strategies in emerging markets.

In our findings, it is evident that the influence of the previous day's close, low, high, and opening price, along with the MA values on the close price of exchange rates, varies significantly across diverse quantiles. This observation indicates the dynamic nature of exchange rates and enhances understanding of the relationship between technical indicators and exchange rates. Following the fitting of the reference GLD regression line, QR models were derived under two conditions: Case-I with a fixed intercept and Case-II allowing all coefficients to vary. In summary, the outcomes of Case-I outperform those of Case-II, as evidenced by the minimum error values. In general, the observed dynamics of the EURO/LKR and GBP/LKR were effectively represented by the QR model fitted using a 0.1 quantile, and for USD/LKR, the QR model with a central quantile exhibited the minimal errors. The application of GLD-based QR models presents a viable approach for predicting exchange rates in Sri Lanka, thereby contributing to the overarching goal of fostering economic growth within the nation. This approach not only improves the accuracy of exchange rate forecasting but also offers valuable insights for policymakers and investors, particularly in the context of Sri Lanka's economic challenges due to LKR depreciation.

While this study provides valuable insights into the heterogeneous effects of technical indicators on exchange rates using GLD-based Quantile Regression QR models, the limitations of this work are as follows: Firstly, the scope of the study is limited to historical data of specific technical indicators, which may not fully capture all factors influencing exchange rate movements. Additionally, while the GLD-based QR model is reliable and versatile, it may still face challenges in accurately modelling extreme quantiles or capturing sudden, unforeseen market shifts. The study's focus on Sri Lanka's LKR context may limit the generalizability of the findings to other countries or currencies with different economic conditions and dynamics. While the current study utilizes the traditional QR model to investigate the heterogeneous effects of technical indicators on exchange rates, integrating QR neural network methods could further enhance the predictive power and reliability of the analysis as QR neural networks can model complex, non-linear relationships and interactions among variables, potentially uncovering deeper insights into the dynamics of exchange rate movements.

5. Acknowledgement

This study is supported by the University Research Grant of the University of Kelaniya (Grant No: RP/03/02/08/01/2021) and Newly Recruited Probationary Lecturer (NRPL) grant of the University of Peradeniya (Grant No: NRPL/2023/03/S).

6. References

Basnayake, B. R. P. M., & Chandrasekara, N. V. (2022). Forecasting exchange rates in Sri Lanka: a comparison of the double seasonal autoregressive integrated moving average models (DSARIMA) and SARIMA models. Journal of Science of the University of Kelaniya, 15(2), 192–209. https://doi.org/10.4038/josuk.v15i2.8067

Freimer, M., Kollia, G., Mudholkar, G. S., & Lin, C. T. (1988). A study of the generalized tukey lambda family. Communications in Statistics - Theory and Methods, 17(10), 3547–3567. https://doi.org/10.1080/03610928808829820

Huang, A. Y. H., Peng, S. P., Li, F., & Ke, C. J. (2011). Volatility forecasting of exchange rate by quantile regression. International Review of Economics and Finance, 20(4), 591–606. https://doi.org/10.1016/j.iref.2011.01.005

Kleopatra, N. (2008). The behaviour of the real exchange rate: Evidence from regression quantiles. Journal of Banking and Finance, 32(5), 664–679. http://hdl.handle.net/10419/153101

Lewis, C. D. (1982). Industrial and business forecasting methods: A practical guide to exponential smoothing and curve fitting. Butterworth Scientific.

Rodríguez del Águila, M. M., & Benítez-Parejo, N. (2011). Simple linear and multivariate regression models. Allergologia et Immunopathologia, 39(3), 159–173. https://doi.org/10.1016/j.aller.2011.02.001

Su. (2015). Flexible parametric quantile regression model. Statistics and Computing, 25(3), 635–650. https://doi.org/10.1007/s11222-014-9457-1

Su. (2016). Fitting Flexible Parametric Regression Models with GLDreg in R. Journal of Modern Applied Statistical Methods, 15(2), 768–787. https://doi.org/10.22237/jmasm/1478004240

Su, X., Zhu, H., You, W., & Ren, Y. (2016). Heterogeneous effects of oil shocks on exchange rates: evidence from a quantile regression approach. SpringerPlus, 5(1). https://doi.org/10.1186/s40064-016-2879-9

Tsai, I. C. (2012). The relationship between stock price index and exchange rate in Asian markets: A quantile regression approach. Journal of International Financial Markets, Institutions and Money, 22(3), 609–621. https://doi.org/10.1016/j.intfin.2012.04.005

Zhang, D., Wang, X., Gao, L., & Gong, Y. (2021). Predict and Analyze Exchange Rate Fluctuations Accordingly Based on Quantile Regression Model and K-Nearest Neighbor. Journal of Physics: Conference Series, 1813(1). https://doi.org/10.1088/1742-6596/1813/1/012016

DOI:https//doi.org/10.22452/mjs.vol44no3.7
Malaysian Journal of Science 44(2): 64-72 (September 2025)