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Research Article

Forecasting Exchange Rate of Pakistan Using Time Series Analysis

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Exchange rates are crucial in regulating the foreign exchange market's dynamics. Because of the unpredictability and volatility of currency rates, the exchange rate prediction has become one of the most challenging applications of financial time series forecasting. This study aims to build and compare the accuracy of various methods. The time series model Auto-Regressive Integrated Moving Average (ARIMA) and Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) are utilized to forecast the daily US dollar to Pakistan rupee currency exchange rates (USD/PKR). Lagged observations of the data series and moving average technical analysis are used in both models. Explanatory factors were used as indicators, and the prediction performance was assessed using a variety of commonly known statistical metrics. These statistical metrics suggested the presence of conditional heteroscedasticity. Thus, the process turns to capture the volatility effect of conditional heteroscedasticity through GARCH modeling. It may be inferred based on the results of tentative models; that the ARCH model outperforms the GARCH model in terms of predicting the USD/PKR exchange rate.

1. Introduction

The phrase "exchange rate" describes the value of a currency unit concerning other currencies [1]. It is essential for every international business transaction and hence plays a crucial part in any developing country's economy. Furthermore, it is necessary for all aspects of international economic relations because it encompasses commerce and currency speculation [2]. All preceding arguments are based on the concept that, with the development of a country and the advancement of government, the foreign exchange rate is dynamic and may be projected to obtain information about the country's economic situation [3]. The currency rate significantly impacts the economic operations of emerging countries. Exchange rate forecasting is essential for such countries in terms of economic empowerment and studying economic swings [4].

Pakistan is a developing country facing a continuous decrease in dollar exchange rates. Pakistan's currency is losing its value gradually concerning dollar price as in 1990. It was 21.71 PKR on a dollar, while in 2000, it became equal to 53.65 PKR. In 2010, there was a further fall in the value of the Pakistani currency to 86.05 PKR. Lately, in 2021, the US dollar got a record high exchange rate of 176 PKR in interbank rates. Hence, in the last four decades, the Pakistan currency deteriorated against US dollar, losing its worth more than eighteen times [5].

In the beginning, Pakistan's currency value was not so depressed due to inconsistent government policies, economic devaluation, and government instability. The

Pakistani currency started losing its value rapidly to other currencies, especially the US dollar and British pounds [6].

Several causes led to the depreciation of the Pakistani currency. Still, the most significant ones include the trade imbalance, stagnant exports, increased imports, and increased domestic consumption that led to greater demand for dollars. Furthermore, the budget deficit and balance of payments situation in Pakistan are not encouraging. In the financial year 2017–18, Pakistan faced almost \$12 billion in deficit in the balance of payments, which represents 4% of GDP, according to media sources quoted by financial experts. Pakistan's foreign exchange reserves have fallen from \$17.4 billion in 2017 to \$12.1 billion due to an increase in the current account deficit. To fill the gap left by a declining currency reserve, countries must raise their exports, which will likely rise because of the currency's depreciation. In addition, media reports claim that the currency was allowed to depreciate because of "payment pressure."

The global economy and financial markets have been shaken due to the COVID-19 pandemic. Prevention methods such as social distance and lockdowns have been adopted, but such policies were costly in the form of lower sales and even permanent closure of different firms. Due to the COVID-19 financial losses, the worldwide stock exchange markets were also affected. The world stock markets have witnessed the worldwide contagion caused by the pandemic, and Pakistani stock markets are one of the exchanges that have been affected [7].

Pakistan's currency depreciation faces many pressures. Pakistan's debt has to increase as the exchange rate faces devaluation [8]. Moreover, due to exchange rate depreciation, Pakistanis face high costs of daily routine items. Because of the severe exchange rate fluctuations, the trade also faces crises, and many traders' businesses break down and crash [9]. Even international travel is also disturbed by exchange rate fluctuations. Furthermore, the government also had to make payments of loans, which put pressure on foreign currency reserves [10].

Besides, it is not easy work to predict the upcoming exchange rates. For upcoming circumstances related to the exchange rate, the researchers forecast the exchange rate. Time series analysis is one of the most essential and beneficial techniques to predict the exchange rate [11]. To the best of our knowledge, no recent study forecasts the exchange rates in Pakistan. Therefore, in this article, we will predict the exchange rate of the US dollar for the future period. This prediction would help economists, policymakers, and businessmen to make relevant policies and take investment decisions accordingly.

2. Literature Review

Literature has a few studies representing exchange rate forecasting using different modeling techniques. Awan et al. [12] investigated the monthly data of the Pakistan rupee (PKR) exchange rate with the US Dollar (USD) from January 1982 to April 2010. The authors captured the long- and short-run behavior and diagnosed the relation between exchange rate and relative monetary variables using the ARDL approach. Khan et al. [5] captured the volatility behavior of exchange rate through the GARCH (1, 1) procedure and utilized different significant currencies along with PKR for a one-step forecast. They concluded that international vehicle currency is more favorable in Pakistan's context. Rasheed [13] focused on forecasting the exchange rate values of USD and PKR through ARIMA modeling using a data range of five years, from April 2014 to 31 March 2019. Their study exhibits that ARIMA (1, 1, 9) is the most fitted model for forecasting. The time series techniques exponential models, Naïve, ARIMA, and ARDL co-integration, conclude that the exponential modeling is most effective. Naeem et al. [14] collected the exchange rate data of PKR/USD from a forex website. The Pakistan business community discusses financial work to propose five machine learning approaches for forecasting. The techniques were simple logistic classifier, random forest, bagging, naïve Bayes, and support vector machine and concluded the highest forecast accuracy of 82.14% through simple logistic.

Despite their utility, the studies mentioned above do not discuss ARIMA and ARCH modeling, which is also suitable for exchange rate forecasting. Moreover, the previous studies do not provide evidence related to the volatility of the daily exchange rate, which logically and statistically appears in the daily observations. On the contrary, they give the relation and monthly prediction of the exchange rate of PKR through the best-fitted model.

Adetunde et al. [15] described the Ghana Cedi exchange rate against US dollar to forecast the future by employing monthly data from January 1994 to December 2010. Their results are based on ARIMA (1, 1, 1) best fitted through BIC (9.11), MAPE (0.915), RMSE (93.873), and r-square 1.000 criteria and found the depreciation trend faced by the Ghana currency. They applied a one-step ahead forecast employing the GARCH (1, 1) model. Liu and Lv [16] determined and forecasted the USD index volatility through ARIMA and GARCH models and discovered the difference between these two forecast approaches. They conclude that the ARIMA time series model is appropriate for short-term forecast purposes, such as month prediction. By contrast, the GARCH model is a proper technique for the longer-term forecast.

Quinta et al. [17] studied rupiah forecasting on US dollar through past values of duration 4 January 2010 to 24 June 2016. They employed ARIMA modeling and provided four stages, that is, dataset preparation, data preprocedural, ARIMA modeling, and accuracy tests. Their conclusion provided 98.74% accuracy.

Yildiran et al. [1] used 3069 daily observations from 3 January 2005 to 8 March 2017 to forecast the Turkish lira for both the long and short term. For this purpose, they found that ARIMAs outperform for short- and long-term modeling.

The purpose of this article is to predict the economic status of Pakistan by forecasting the Pakistan exchange rate with US dollars. The exchange rates have a high impact on economic growth, the trade market, government debt, inflation rates, and remittances. Therefore, organizations and individuals related to the above factors can take advantage of the prediction of the stability of the currency. The Pakistan government, before starting any development project, monitors the policies that can affect the exchange rate. Hence, this research is expected to help the national level keep an eye on the trend and stability of the exchange rate in the coming period. This study is also worthwhile for economists and policymakers as the sudden shocks in the exchange rate cause fluctuations in economic growth. Exchange rate volatility is a practical term to understand and predict as exchange rate volatility does not affect the market of developed countries to a great extent, however. The exchange rate volatility highly affects the developing countries, and Pakistan is one of them. Therefore, this study is helpful in every aspect that affects the economic growth of Pakistan.

Under this structure, although there are limitations regarding ARIMA, ARCH, and GARCH models, this article forecasts Pakistan's currency exchange rate with the US dollar and Chinese Yuan from the observation from 1 January 2018 up to 24 April 2021.

3. Data Description

Data were collected from an authentic source from the State Bank of Pakistan about the exchange rate in Pakistan. This information comprises two variables, US dollars and Chinese Yuan. The data have a duration from 1 January 2018 to 24 April 2021. The period is based on daily observations, having two components, one is the dependent variable, and the other one is an independent variable as the exchange rate is part of the economic time series, which is considered as a dependent variable. By contrast, time is said to be an independent variable.

Figure 1 exhibits the pattern of original prices of the PKR exchange rate with USD and CNY for January 2018 to April 2021. Such a pattern explains the increasing trend in the series, which reveals the random walk of the index.

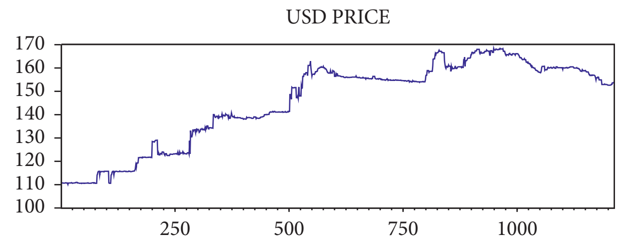

Figure 1: Time plot of $\mathbf{USD_tCNY_t}$.

4. ARIMA Method

Stationary is the basic assumption to be fulfilled for the time series forecasting, while other specified conditions are the mean should be independent over time $(E(a_t) = \mu)$ and the variance among consecutive observations should be constant $(\mathrm{COV}(a_t, a_{t-1}) = \varphi_l)$.

$$v_t = \theta_1 v_{t-1} + \ldots + \theta_p v_{t-p} + z_t,$$
$$v_t = \theta(\beta)^{-1} z_t, \tag{1}$$

$$v_t = b_t - \vartheta_1 b_{t-1} - \ldots - \vartheta_q b_{t-q},$$
$$v_t = \vartheta(\beta) b_t, \tag{2}$$

$$\begin{aligned} v_t &= \theta_1 v_{t-1} + \ldots + \theta_p v_{t-p} + b_t - \vartheta_1 b_{t-1} - \ldots - \vartheta_q b_{t-q}, \\ v_t &= \frac{\theta(\beta)}{\vartheta(\beta)} b_t. \end{aligned} \tag{3}$$

Here, the AR (p) model is represented by equation (1) with p parameters, and MA (q) model is represented by equation (2) with q parameters. Hence, the combination of both models ARMA (p, q) can be illustrated as (1) with p and q parameters.

$$\varphi(\beta)\nabla^d v_t = \varnothing_0 + \varnothing(\beta) b_t. \tag{4}$$

This equation is applied when the original series is not stationary at its level. A transformation is needed, such as differencing. Further, if the series is ensured stationary at the first difference, then it provides that the original series is comprised of unit root and defined as $I(1)$. Generally, if it is stationary at more than 1 difference, it is represented by d parameters. In such a case, equation (4) specifies the ARIMA (p, d, q) model with p, d, and q parameters [18].

5. ARCH Method

Engle introduced a model in 1982; the autoregressive conditional heteroscedasticity model is the first procedure under the systematic framework regarding volatility modeling. Through the basic idea of the dependent shock of asset return c_t and uncorrelated serially, dependency of c_t with the quadratic function, lagged values can be examined. The ARCH effect can be determined in the following details:

$$\begin{aligned} c_t &= \sigma_t \varepsilon_t, \\ \sigma_t^2 &= \alpha_0 + \alpha_1 a_1^2 + \ldots + \alpha_s a_{t-s}^2. \end{aligned} \tag{5}$$

Here, practically, standardized t-distribution and standard normal distribution are followed by ε_t and $\alpha_0 \rangle 0$ and $\alpha_s \rangle 0$ for $k \rangle 0$. Although the condition of a system of a random variable that is identically independently distributed (iid), random variables are also followed. Moreover, the regularity condition regarding the coefficient α_i of ARCH effect is that c_t conditional variances are finite. For the c_t innovation, the large past shocks $\left\{c_{t-k k=1}^{2\quad 2}\right\}$ are used to attain significant conditional variances σ_t^2 [19].

At the same time, the study of [20] revealed the ARIMA modeling limitations such as modeling models, which is assumed to be linear. It is mainly reasoned that in real-world time series, linearity approximation does not provide acceptable outcomes by simply saying, ARIMA modeling does not offer coverage to account for the data pattern of nonlinearity. Such an argument implies that to forecast time series of high volatility; there would be an accuracy lack. Comparatively, to cover this accuracy, a hybrid model such as the fuzzy artificial neural network model is designed as it is capable of fitting nonlinear data for forecasting accuracy than ARIMA modeling [21].

Moreover, Hsu et al. [22] latest study provides an argument that to predict time series, an artificial neural network (ANN) is supremacy in comparison with econometric models such as ARIMA modeling and generalized autoregressive conditional heteroscedasticity (GARCH). Moreover, their study got concluded evidence that the best machine learning mechanisms (MLM) perform better than the best econometric models (EM) through the literature of 30 types of research, some in the market of FX and others in the market of finance [23].

Tlegenova [11] concluded that in the forecast of Indian currency (INR) with significant currencies of the world, EM, such as ARIMA modeling, outperforms ANN and FNN. Hence, such a study highlighted the significance of ARIMA modeling in forecasting the exchange rates in the current world of research [24].

6. Results

In this structure, after gaining the knowledge about ARIMA method linearity assumption limitation, the main target of this study is to forecast the US dollar/Pakistan rupee (USDPKR) by statistical time series techniques and utilize the observations from 1 January 2018 to 24 April 2021. For this purpose, this study selects the EViews 10 software for applying all statistical methods.

6.1. Descriptive Statistics. For achieving the target of forecasting, the routine time series is transformed based on these steps: firstly, the original series (exchange rate of PKR with USD) is shown by USD_t and the first difference between the original series is represented by $d\mathrm{USD}_t$. As we aim to predict the series in the long term, the descriptive of USD_t and $d\mathrm{USD}_t$ is described below and illustrates Figure 2, which depicts the graph of the mentioned series over time.

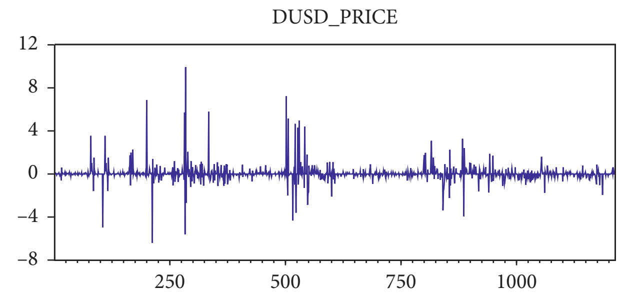

Figure 2: The graph of dUSD_t series concerning time.

Table 1: Descriptive statistics for USD_t and $d\mathrm{USD}_t$ time series.

	USD_t	dUSD_t
Mean	145.5941	0.035940
Median	154.6000	0.000000
Maximum	168.3663	9.935090
Minimum	110.0740	−6.394855
Standard deviation	18.01156	0.809751
Skewness	−0.680844	2.900372
Kurtosis	2.078133	46.75599
Jarque–Bera test	136.6664	98385.90
Probability	0.000000	0.000000
Sum	176605.7	43.55964
Sum Sq. deviation	393192.6	794.0484
Observations	1213	1212

Commonly, literature provides evidence of a significant difference between the maximum and minimum observations in the exchange rate series. At the same time, in this study, the difference is not too substantial and provides a reasonable range. The standard deviation demonstrates the fluctuation of high levels for all the USD_t and dUSD_t series. The original series provide evidence of negative skewness that explains the left tail is specifically extreme, which describes the nonsymmetric pattern of the original series and the transformed series. The series dUSD_t kurtosis is described as fat-tailed that statistically said leptokurtic, as the kurtosis terms exceeded the normal value 3. Contrastingly, the original series USD_t are platykurtic as its kurtosis statistic given in Table 1 is less than 3. Moreover, all considered series in this study USD_t and dUSD_t series are said to be non-normal through the value of Jarque–Bera test representing the rejection of the null hypothesis even at the 1% significance level.

6.2. Stationarity. The augmented Dickey–Fuller test introduced by Dickey and Fuller in 1981 is used here to diagnose stationarity in the time series of ARIMA and ARCH/GARCH modeling (Tables 2–4). This is so because ARIMA represents an uptrend without any ambiguity; therefore, the parameter of trend is added to the ADF equation.

$$\begin{aligned} \nabla v_t &= \delta v_{r-1} + b_0 + b_1 t + z_t, \\ \nabla v_t &= \left(\delta v_{r-1} + z_t\right). \end{aligned} \tag{6}$$

For these equations, the hypothesis can be defined as a null and alternative hypothesis as follows:

H_o = the series is said to be nonstationary
H_1 = the series is said to be stationary

The results computed through the ADF test exhibit the original series USD_t, which fails to reject the null hypothesis in each case, that is, at level, intercept, with level and intercept, and without trend and intercept or intercept. This output representation means that the original series at its level is not stationary. Therefore, the next step is to transform to make the series stationary. Hence, dUSD_t series are computed where the difference is taken and again diagnose whether the stationarity is now present or not. Through ADF test analysis, it has now appeared that dUSD_t is stationary as it is succeeded in rejecting the null hypothesis as the computed probability is less than 1% significance for each case, that is, with level intercept, with level and intercept, and without trend and intercept or intercept, while the dUSD_t is utilized for the further analysis.

6.3. Correlogram of $\mathbf{USD_t}$ *Series in Level.* The correlogram for USD_t and dUSD_t series presented in Figure 3. This representation of the correlogram of USD_t series exhibits that

Table 2: ADF test for USD_t and $dUSD_t$ at levels intercept.

	ADF statistic	Probability	Critical values		Results' interpretation
USD_t	−2.0504485	0.2653	−3.435536	@1% level	Nonstationary
			−2.863718	@5% level	Nonstationary
			−2.567980	@10% level	Nonstationary
$dUSD_t$	−43.56188	0.0001	−3.435536	@1% level	Stationary
			−2.863718	@5% level	Stationary
			−2.567980	@10% level	Stationary

Table 3: ADF test for $\mathbf{USD}_t$ and $\mathbf{dUSD}_t$ at levels trend and intercept.

	ADF-statistic	Probability	Critical values	Results' interpretation	
USD_t	−0.492292	0.9839	−3.965642	@1% level	Nonstationary
			−3.413527	@5% level	Nonstationary
			−3.128812	@10% level	Nonstationary
$dUSD_t$	−43.66697	0.0000	−3.965642	@1% level	Stationary
			−3.413527	@5% level	Stationary
			−3.128812	@10% level	Stationary

Table 4: ADF test for $\mathbf{USD}_t$ and $\mathbf{dUSD}_t$ without trend and intercept or intercept.

	ADF-statistic	Probability	Critical values	Results' interpretation	
USD_t	1.663901	0.9770	−2.566873	@1% level	Nonstationary
			−1.941085	@5% level	Nonstationary
			−1.616523	@10% level	Nonstationary
$dUSD_t$	−43.47014	0.0001	−2.566873	@1% level	Stationary
			−1.941085	@5% level	Stationary
			−1.616523	@10% level	Stationary

these series at its level are not performing stationarity. In this case, the figure reveals the nonstationarity of the study series at its level and concludes that a transformation is needed here. While the representation of correlogram of USD_t, CNY_t series exhibits that these series perform stationarity at first, which is the primary and essential assumption to be filled in terms of time series. Additionally, correlogram represents the Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF), which are the tools used for the identification of Moving Average (MA) and Auto-Regressive (AR) modeling parameters, respectively.

In this case, this figure reveals the stationarity of these series. It provides hidden hints for the parameter selection of Moving Average (MA) and Auto-Regressive (AR) modeling through Auto Correlation Function (ACF) and Partial Auto Correlation Function (PACF).

7. Methodology

A specific procedure, autoregressive integrated moving average (ARIMA) under time series forecasting, was introduced by Box and Jenkins. The steps of model identification, parameter estimation, and model checking are part of this approach.

7.1. Model Specification and Application. A variety of criteria are available for the order determination of AR and MA process for ARIMA modeling in the literature study. Hence, various diagnostic tools for the same type of data determine different numbers of orders. The most significant coefficients that are the highest adjusted R^2 with the lowest sigma square, volatility, and the lowest Akaike information criterion, most probably using Akaike information criterion (AIC) and Schwartz information criterion (SIC), are selected for the diagnosis of fitted ARIMA modeling along with parameters.

The Table 5 represents the outcome of tentative models about the USD/PKR first difference. ARIMA (1, 1, 1) is the most appropriate model. As it comprises the most significant coefficients, the highest adjusted R-square is 0.051190 with the least volatility through sigma square 0.620074. Similarly, the AIC and SIC terms represent the values 2.36661 and 2.383443, respectively. Until this stage, the best-fitted ARIMA model is obtained from the above tentative models.

Further next stage is to diagnose either still any information left to explore or not. Therefore, if there is no information left behind to explore, then the residual diagnostic correlogram is considered flat, which means that the residuals should be bounded with the standard error represented by the dotted line at the correlogram, while its ACF and PACF terms should be stationary. Therefore, the following procedure explains the diagnostic tests of the best-fitted ARIMA modeling.

7.2. Diagnostic Tests of the Selected ARIMA Model. In this context of the study, the below table represents the outcome of ACF, PACF, and p-value that are attained through the

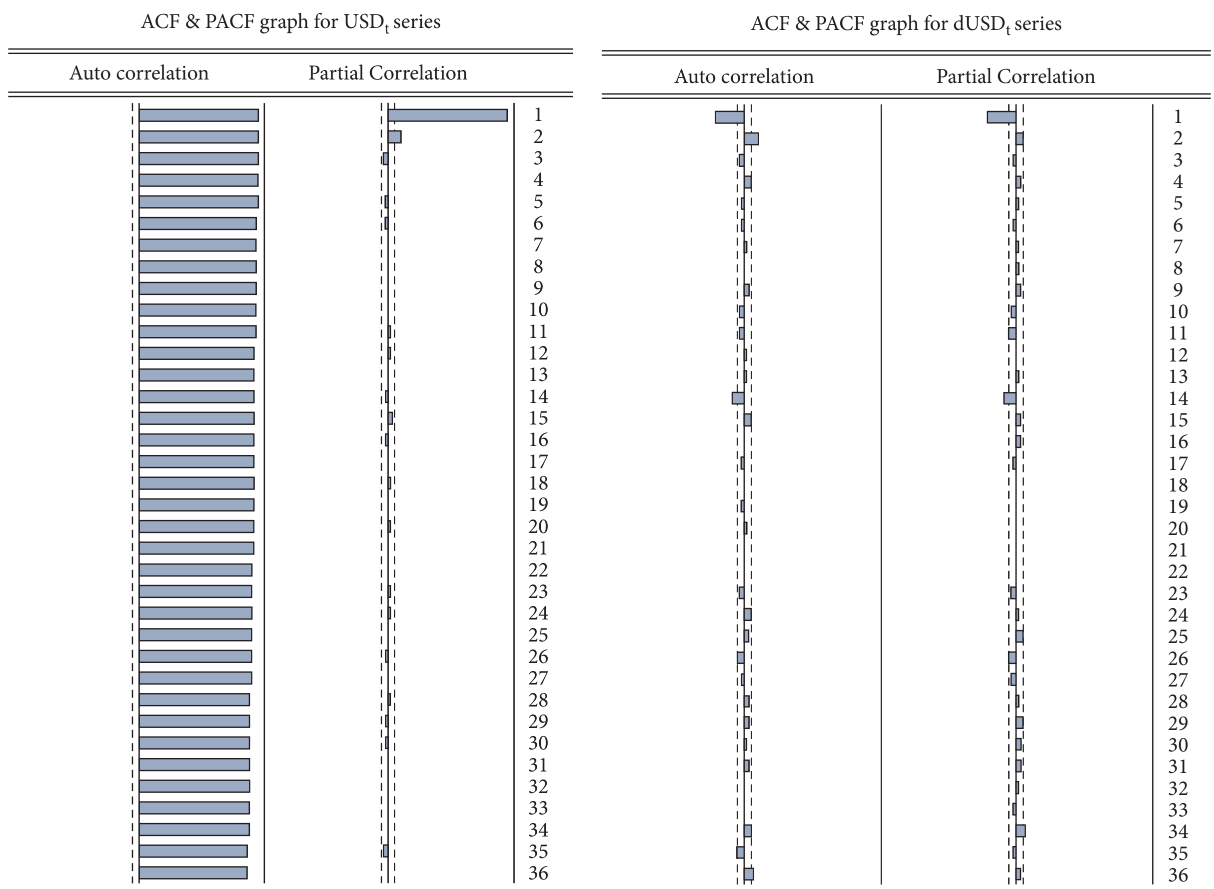

Figure 3: Correlogram for USD$_t$ and dUSD series.

Table 5: USD/PKR model estimation results.

ARIMA models	Sig. Coefficients	Sigma square	Adjusted $\mathbf{R}^2$	AIC	SIC	Durbin–Watson stat
1, 1, 1	2	0.620074	0.051196	2.366611	2.383443	2.00503
1, 1, 2	2	0.620766	0.050137	2.367723	2.384555	1.996646
1, 1, 11	1	0.622144	0.048029	2.369947	2.386779	1.970383
1, 1, 14	2	0.619123	0.052651	2.365134	2.381965	1.969805
2, 1, 1	2	0.620435	0.050645	2.367191	2.384022	1.997569
2, 1, 2	1	0.646328	0.011024	2.408053	2.424885	2.394211
2, 1, 11	1	0.646404	0.010908	2.408177	2.425008	2.394857
2, 1, 14	2	0.641811	0.017936	2.401126	2.417958	2.386060
3, 1, 1	1	0.627268	0.040189	2.378127	2.394959	2.039712
3, 1, 2	1	0.647268	0.009586	2.409500	2.426332	2.397501
3, 1, 11	1	0.653080	0.000693	2.418436	2.435267	2.431091
3, 1, 14	2	0.648562	0.007606	2.411572	2.428404	2.422456
14, 1, 1	2	0.623475	0.045993	2.372134	2.388965	2.039123
14, 1, 2	2	0.642211	0.017323	2.401755	2.418587	2.390340
14, 1, 11	1	0.649540	0.006109	2.413084	2.429915	2.438735
14, 1, 14	2	0.642525	0.016843	2.402827	2.419658	2.440060

residual diagnostic Q-statistic test running on the ARIMA (1, 1, 1) model, which has been chosen from the above-mentioned diagnostic criterion to forecast USD/PKR foreign exchange rate.

Table 6 represents that the residual correlogram for ARIMA (1, 1, 1) is flat as its ACF and PACF values are less than 1, which is relatively small. Its p-values are also representing the insignificant values that are greater than 1% and 5% significance levels. Hence, showing ARIMA (1, 1, 1) is stationary. Moreover, Q-state probability reveals the existence of autocorrelation as all these probabilities are more significant than 1% and 5% (except the probability at lag 36). Hence, this gives an alarming situation in the presence of conditional heteroscedasticity.

7.3. Diagnostic Tools for Heteroscedasticity Detection in the Fitted Model. Further, due to the limitations of ARIMA modeling, this research technique moves toward ARCH modeling to detect conditional heteroscedasticity. Due to this reason, the ARCH effect is tested after the selection of the best-fitted ARIMA modeling to diagnose whether the fitted model is comprised of conditional heteroscedasticity or not. For this purpose, this paper utilizes Autoregressive Conditional Heteroscedasticity-LaGrange Multiplier (ARCH-LM) test introduced by Engle in 1982, having the following pair of hypotheses:

H_o = there is no existence of the ARCH effect in a particular series

H_1 = there is the existence of the ARCH effect in a particular series

The decision of the ARCH-LM test is based on the following point; if the obtained p-value is less than the 1% significance level, then the evidence is provided to reject the null hypothesis (Table 7). Contrastingly, if the p-value is more significant than the level of significance, otherwise it failed to reject the null hypothesis.

Based on this interpretation, the outcome of the ARCH-LM test for the USD/PKR series reveals that the null hypothesis is rejected. That exhibits the presence of the ARCH effect in the study series. While through these results, it is concluded that the variance coefficient increases concerning time.

That exhibits the presence of the ARCH effect in the study series. Consequently, providing evidence for the requirement of variance equation gives conditional heteroscedasticity. Therefore, the analysis will progress toward the ARCH/GARCH time series technique and then again diagnose the conditional heteroscedasticity through the ARCH-LM test to confirm the absence of conditional heteroscedasticity.

Table 6: Residual diagnostic test of ARIMA (1, 1, 1) for USD/PKR series.

Lags	ACF	PACF	Q-stat	Probability
1.	−0.000	−0.000	0.0002	0
2.	0.001	0.001	0.0009	0
3.	0.013	0.013	0.2095	0.647
4.	0.031	0.031	1.3707	0.504
5.	0.005	0.005	1.4010	0.705
6.	−0.014	−0.014	1.6254	0.804
7.	0.024	0.023	2.3276	0.802
8.	0.018	0.017	2.7021	0.845
9.	0.025	0.025	3.4624	0.839
10.	−0.046	−0.046	6.0455	0.642
11.	−0.039	−0.041	7.8773	0.547
12.	0.023	0.021	8.5009	0.580
13.	−0.006	−0.006	8.5458	0.664
14.	−0.084	−0.081	17.23	0.141
15.	0.052	0.055	20.583	0.082
16.	0.017	0.014	20.930	0.103
17.	−0.018	−0.017	21.339	0.126
18.	−0.001	0.006	21.342	0.166
19.	−0.007	−0.007	21.399	0.209
20.	0.013	0.009	21.594	0.250
21.	0.002	0.004	21.598	0.305
22.	−0.011	−0.010	21.740	0.355
23.	−0.036	−0.034	23.338	0.326
24.	0.048	0.038	26.220	0.242
25.	0.030	0.029	27.348	0.241
26.	−0.073	−0.063	33.938	0.086
27.	−0.027	−0.030	34.827	0.091
28.	0.041	0.032	36.869	0.077
29.	0.037	0.046	38.598	0.069
30.	0.024	0.030	39.294	0.076
31.	0.038	0.037	41.083	0.068
32.	0.005	0.000	41.116	0.085
33.	0.015	0.007	41.414	0.100
34.	0.052	0.057	44.764	0.066
35.	−0.028	−0.022	45.726	0.069
36.	0.055	0.045	49.538	0.041

7.4. Parameter Estimation of ARCH/GARCH Time Series Modeling. ARCH modeling is one of the basic techniques, which explicit that fluctuations in variance concerning time in time series. This modeling is used to explore the difference between unconditional and conditional variance, commonly termed conditional heteroscedasticity. In finance, ARCH modeling is widely used to estimate risk through volatility modeling. Therefore, ARCH modeling is applied for USD/PKR series.

For the USD/PKR exchange rate series, ARCH modeling output is mentioned in Table 8. This table comprises three portions. One is for the mean equation, the second is for the variance equation, and the third one reveals the criterion for selecting fitted models. Hence, the mean equation exhibits the insignificance of AR and MA modeling parameters and provides the probability greater than 1% level of significance and although strong evidence of their insignificance is attained. Next, the variance equation exhibits the ARCH parameter that is enormously significant through the probability of less than 1% level of significance, and the constant term of the variance equation is also significant. Further, the third portion exhibits the AIC and SIC values, which are negative and smallest as well for the model selection.

In Table 9, GARCH (1, 1) model is applied to estimate USD/PKR exchange rate series. Model parameter estimation results are shown in Table 8. It is observed that $0.035492 + 0.936849 = 0.9972 < 1$, providing evidence that the process meets the unit root test and parameter constraints. AIC value is 2.093855, and SC value is 2.119119, which are small and considered that the model is better fitted. The GARCH modeling is formed below:

$$\begin{aligned} r_t &= (0.010702 - 0.649159) + 0.510485, \\ h_t &= \left(0.016751 + -0.035492\varepsilon_{t-1}^2\right) + 0.936849h_{t-1}. \end{aligned} \tag{7}$$

7.5. ARCH-LM Test for Residuals. The below-mentioned Table 10 helps us to explore the series USD/PKR series' hidden knowledge about the volatility. As in the previous content, ARCH/GARCH models are fitted to make the conditional heteroscedasticity absent, after which, again, we

Table 7: ARCH-LM test for the residuals of USD/PKR series.

ARCH-LM (F-statistic)	Obs R-squared	Prob. F (1,1209)	Prob. Chi-square (1)
21.85163	21.49920	0.000	0.000

Table 8: Estimation of ARCH model for USD/PKR series.

Variable	Coefficient	Std. Error	Z-statistic	Probability
Mean equation				
C	0.035321	0.014839	2.380313	0.0173
AR (1)	−0.266454	0.128966	−2.066075	0.0388
MA (1)	0.059652	0.125105	0.476818	0.6335
Variance equation				
E	0.440444	0.004285	102.7761	0.0000
ARCH (1)	0.406723	0.40277	10.09826	0.0000
R-squared	0.050459		Mean dependent var	0.035998
Adjusted R-squared	0.048887		SD-dependent var	0.810083
S.E. of regression	0.790034		Akaike information criteria (AIC)	2.185650
Sum squared residual	753.9771		Schwartz criterion	2.206704
Log-likelihood	−1318.411		Durbin−Watson stat	2.193577

Table 9: Estimation GARCH model for USD/PKR series.

Variable	Coefficient	Std. Error	Z-statistic	Probability
Mean equation				
C	0.010702	0.020673	0.517690	0.6047
AR (1)	−0.649159	0.174864	−3.712370	0.0002
MA (14)	0.510485	0.183957	2.775029	0.0055
Variance equation				
E	0.016751	0.000702	23.87087	0.0000
ARCH (1)	0.035492	0.002188	16.22417	0.0000
GARCH (1)	0.936849	0.002323	403.2149	0.0000
R-squared	0.047442		Mean-dependent var	0.035998
Adjusted R-squared	0.045865		SD-dependent var	0.810083
S.E. of regression	0.791288		Akaike information criterion (AIC)	2.093855
Sum squared residual	756.3722		Schwartz criterion	2.119119
Log-likelihood	−1261.829		Durbin−Watson stat	2.103367

Table 10: ARCH-LM test for the residuals of CNY/PKR and USD/PKR series.

	USD/PKR series	
	ARCH	GARCH
ARCH-LM (F-statistic)	0.114144	0.602791
Obs∗R-squared	0.114322	0.603488
Prob. F (1,1208)	0.7355	0.4377
Prob. Chi-square (1)	0.7355	0.4373

diagnose the absence/presence of conditional heteroscedasticity through the ARCH-LM test. This test was applied for ARCH and GARCH modeling for both series. Through using this test, it is revealed that for both procedures, ARCH and GARCH attain the absence of conditional heteroscedasticity. In other words, it can be said that the volatility over a particular period is now constant. By contrast, for the USD/PKR series, GARCH modeling provides more significant evidence of attaining the absence of conditional heteroscedasticity than ARCH modeling. The observed R-square of GARCH modeling for the series is significantly higher than the ARCH modeling, that is, 0.603488, respectively.

7.6. Forecast Performance. The models evaluated for USD/PKR are used to explore the upcoming events. These models are also valuable because of their future return forecasting ability. Hence, to diagnose forecasting ability, the researcher uses some criteria for measuring accuracy. The most common measurements that are used for forecasting performance measures are root mean square error (RMSE), mean absolute error (MAE), mean absolute percent error (MAPE), and their inequality coefficient (TIC). This study also uses these criteria, and the forecast performance results are given in Table 11. The model considers being outperformed, which provides the lowest values for measuring these errors. Table 11 output reveals that USD/PKR series

Table 11: Forecast performance of estimated models.

Forecast performance	Models for USD/PKR series	
	ARCH	GARCH
Root mean square error (RMSE)	0.468248[1]	0.635898[2]
Mean absolute error (MAE)	0.350321[1]	0.444160[2]
Mean absolute percent error (MAPE)	0.228121[1]	0.289045[2]
Theil inequality coefficient (TIC)	0.001530[1]	0.002079[2]
Overall rank	1	2

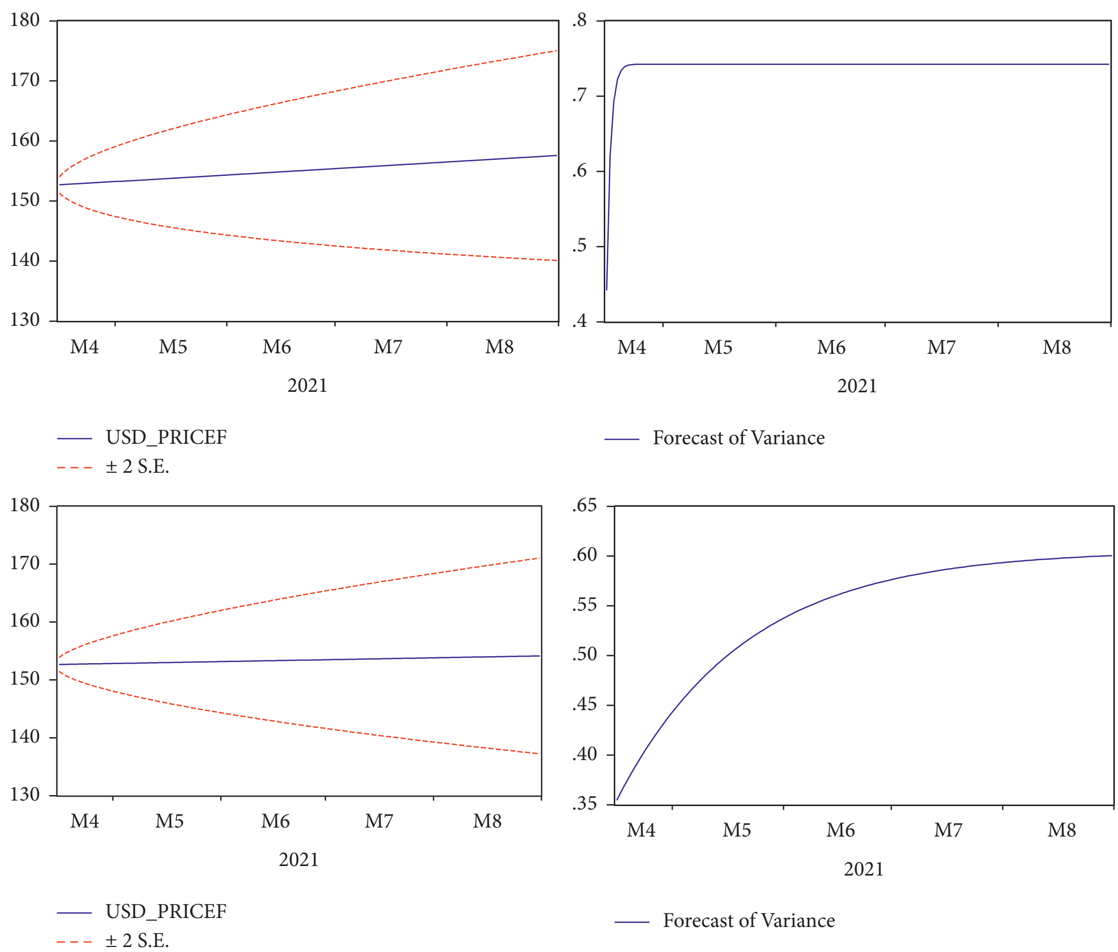

Figure 4: Forecasting in US dollars from 15 April to 31 August.

ARCH modeling performed more significantly than GARCH modeling. Figure 4 represents the volatility of the out-of-sample forecast and USD/PKR exchange rate variance forecast.

8. Discussion

The primary purpose of our study is to forecast the exchange rate because the exchange rate forecast is beneficial for the economy of Pakistan. Exchange rate forecasting plays a vital role in economic growth as it has a high impact on economic growth, trade market, government debt, inflation rates, and remittances. Hence, organizations, as well as individuals that relate to the above factors, can take advantage of the prediction of the stability of the currency. The role of the exchange market is essential in developing countries. In essence, such a market is utilized for currencies trade and is considered an over-the-counter market [25]. Hence, exchange rate prediction is regarded as one of the demanding time series applications [26].

As the current government uses the flexible exchange rate regime, many fluctuations are found in the series used in this article. By contrast, these fluctuations are inherently noisy, nonstationary, and deterministically chaotic. Hence, it is not an easy task to generate a quality forecast.

Moreover, the practical time series are nonstationary, and the case of stationary is a rare one. Therefore, ARIMA modeling of time series is preferable to explore the best-fitted model for forecasting by utilizing this time series technique to forecast.

Furthermore, our study does not limit ARIMA modeling as common the exchange rate series comprises heavy fluctuations that induce conditional heteroscedasticity in the series. Due to this primary reason, this study turns to the GARCH modeling in the presence of conditional heteroscedasticity. GARCH modeling comprises three parameters to allow infinite numbers of square roots that influence the conditional variance. Such features of GARCH modeling make it more economical than ARCH modeling. In other words, GARCH modeling is considered a better fit for time series data modeling, which represents conditional heteroscedasticity and volatility. Gao and Sun [26] and Magnus and Eric Fosu [27] use the GARCH conditional heteroscedasticity modeling to forecast the exchange rate as these models capture the volatility and provide the variance equation for non-constant variance series. The forecasting exchange rate through the GARCH modeling technique provides a better forecast as its fitted values have the most minimum differences from the actual rates as [27] explored for the Ghana stock exchange.

9. Conclusion

By employing daily observations of USD/PKR rate, time series analysis is used to forecast up to the 8th month of 2021. The sample was extended from 1st January 2018 to 27th April 2021. The volatility of USD/PKR series is modeled as the conditional heteroscedasticity commonly present in the financial series. It is explored that the series under study have stylized characteristics like volatility clustering, leptokurtosis, and asymmetric effects. Hence, ARIMA modeling is used initially, and the parameters are selected through AIC, SIC, adjusted R-square, and *R*-square criteria. Then, ARCH-LM test is obtained to diagnose conditional heteroscedasticity. Due to variance volatility, ARCH modeling and GARCH modeling are used. It is concluded that USD/PKR in the case of ARCH modeling outperforms comparatively GARCH modeling. There was a clear upward trend in forecasting the understudy series. USD/PKR exchange rate by ARCH modeling shows an upward trend providing the confidence interval between 175 and 135 PKR almost. While the USD/PKR series through the GARCH model also provides an upward trend but provides a confidence gap between 170 and 135 PKR.

Data Availability

Datasets were derived from public resources website (https://www.sbp.org.pk/) and made available within the article.

Conflicts of Interest

The authors declare that there are no conflicts of Interest.

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