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Forecasting the Turkish Lira Exchange Rates Through Univariate Techniques: Can the Simple Models Outperform the Sophisticated Ones?

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ABSTRACT

The Central Bank of Turkey's policy to decrease the nominal interest rate has caused episodes of severe fluctuations in Turkish lira exchange rates during 2022. According to these conditions, the daily return of the USD/TRY have attracted the risk-taker investors' attention. Therefore, the uncertainty about the rates has pushed algorithmic traders toward finding the best forecasting model. While there is a growing tendency to employ sophisticated models to forecast financial time series, in most cases, simple models can provide more precise forecasts. To examine that claim, present study has utilized several models to predict daily exchange rates for a short horizon. Interestingly, the simple exponential smoothing model outperformed all other alternatives. Besides, in contrast to the initial inferences, the time series neither had structural break nor exhibited signs of the ARCH and leverage effects. Despite that behavior, there was undeniable evidence of a long-memory trend. That means the series tends to keep a movement, at least for a short period. Finally, the study concluded the simple models provide better forecasts for exchange rates than the complicated approaches.

Keywords: exchange rate; forecasting; autoregressive; exponential smoothing; structural break

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INTRODUCTION

In most macroeconomic analyses, the exchange rate has always been an integral part of the macro models because the rate plays a crucial role in determining the export/import ratio, which is one of the fundamental parameters in GDP formation and inflation fluctuations [1]. If there are no transaction costs or trade barriers, the purchasing power parity (PPP) hypothesis states the exchange rate of two currencies equals the ratio of their inflation rates. The hypothesis has been subjected to numerous investigations; however, it has been rejected in most cases. In fact, a PPP-based exchange rate time series that is more stable than the market series can be calculated, and in most cases, the two series are cointegrated. For instance, [2] found out there is no short-term co-movement between those time series, but in the long run, the market rates tend to move toward the PPP rates. Actually, the short-term decoupling happens because more parameters than the inflation rate influence the currency's ratio. In this regard, [3], after conducting several diagnostic tests, concluded that there is a negative long-term nexus between the balance of trade and exchange rate. In contrast, [4] found a strong positive relationship between them; however, in the short run, the correlation could be insignificant or non-linear. In addition to those mentioned factors, foreign debts and credit risk are two other examples of other influential variables [5]. As a result, since there is no universal theorem explaining the short-term relationship between exchange rates and macroeconomic parameters, employing univariate forecasting models would be reasonable, specifically if the daily time series is under investigation. For rationalization, according to the above survey, the inflation rate is one of the most influential parameters affecting the exchange rate path; however, there is no daily data for inflation rates. The only quasi-proxy for the daily rate is the return rate of breakeven inflation, which is the return of the differences between 10-year and 10-year inflation-indexed Treasury bond yields. But this indicator can be considered as inflation expectations rather than the actual rate [6]. However, since Turkey's government has not issued inflation-indexed bonds so far, employing this proxy is impractical. As a result, a multivariate model in the best-case scenario can provide monthly forecasts, which is not desired for daily transactions. Therefore, univariate models are the only feasible alternative.

Throughout the past year, the Turkish lira exchange rate has experienced a massive downward trend. Some parts of the problem can definitely be attributed to the COVID-19 virus pandemic and a drastic fall in foreign income due to the extended lockdowns and almost the ban on entering foreign tourists. On the other hand, in response to the increasing rates of inflation, most countries have increased their nominal interest rates as a tightening monetary policy to battle the higher levels of inflation. For example, the Federal Reserve Bank of the U.S. has gently increased the federal funds rate from 0.25 to 4.0 percent during the past nine months (Federal Reserve Bank of St. Louis).[1] In contrast, the central bank of Turkey has declined the rate several times during that period, especially from 11.5 in August to 7.50 in November of 2022.[2] In conventional monetary theories, a decrease in the interest rate is considered an expanding policy that causes inflation rates to hike drastically. Consequently, it seems Turkey's central bank is following other goals than stabilizing the inflation rate through that policy.

There have always been endless arguments among economists about the forecasting power of non-linear volatility models and linear autoregressive ones. In this regard, [7] stated that the exchange rate time series tend to display a long memory behavior; hence, the ARFIMA models proposed by [8] should be employed for forecasting purposes. In contrast, [9] argued that the GARCH models, in most cases, beat the linear alternative ones. However, in the case of highly fluctuating data, autoregressive models provide better forecasts. In another extensive empirical study, [10] analyzed Jamaica's exchange rates using a collection of GARCH models. They found out the return time series had a long memory characteristic and, at the same time, exhibited evidence of asymmetric volatility behavior. Finally, they concluded that a GARCH model with a leptokurtic distributed error term could provide the best forecast.

Now, the question is: what model can provide the best description of the fluctuating trends of the Turkish lira exchange rates and would obtain the most accurate forecast? From May until November 2022, the interest rate has deliberately declined two times. This monetary policy, from an econometrics point of view, can cause two structural breaks in the overall trend of the overall trend of the time series. Therefore, the possible effect of breakpoints should be considered in model tuning. However, in most forecasting studies, the impact of structural breaks has been neglected. The present study has attempted to provide the best possible short-term forecast for the Turkish lira exchange rates by employing univariate models. It should be mentioned that this study does not want to claim that the multivariate models are inapplicable in daily return forecasts. Although, the macro-econometric models, by definition, were not designed for daily data.

On the other hand, there is a growing tendency among econometricians toward employing highly sophisticated models to forecast financial time series. Among all the models, the first rank belongs to artificial neural networks, at least during the past ten years. For instance, [11–13] has worked exclusively on exchange rate forecasts using hybrid neural networks. However, as professor Friedman stated, the models should be compared based on their forecasting power, not how much they satisfy assumptions or are complicated [14]. In fact, imposing more assumptions to build a complex model makes it unrealistic. Market agents generally do not employ logical and rational trading methods because, in that case, the market should be efficient in the sense of [15] theory. But plenty of studies have shown that financial markets are inefficient. That means most market agents use straightforward calculations, are highly emotional in the sense of herding behavior, and are retrospective with a short decision horizon. As a result, this study has not attempted to forecast the exchange rate through a complicated hybrid model but has tried to test if decreasing the complexity of the model leads to better forecasts and whether the traditional approaches still work well.

The structure of the study is as follows. The second section has provided an initial understanding of time

[1] URL: www.fred.stlouisfed.org

[2] URL: www.tcmb.gov.tr

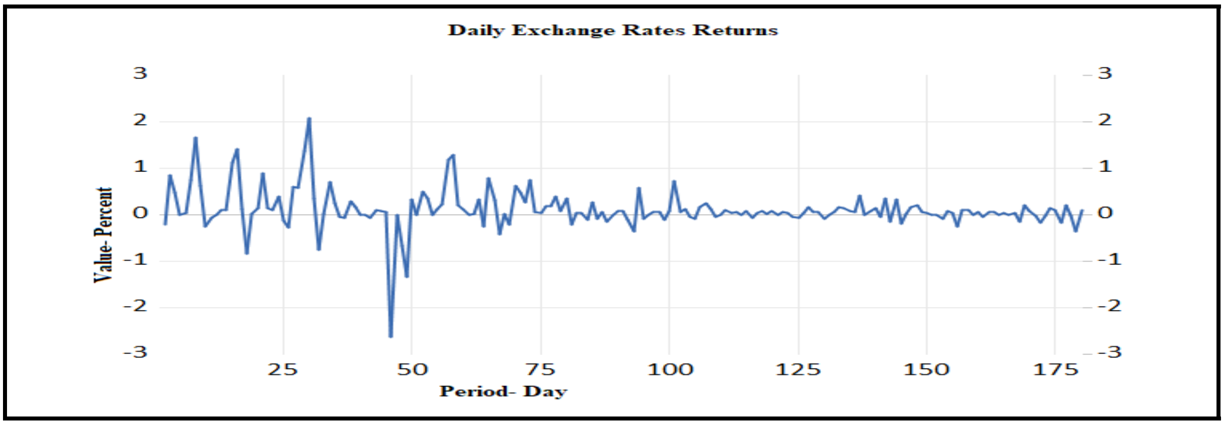

Fig. 1. **Returns Time Series**

Source: Research findings.

series behavior through basic statistical tests and data transformations. In the third part, several models have been estimated concerning the available sample. In the fourth section, and after the out-of-sample forecast, the models have been compared using three goodness-of-fit criteria. Finally, the concluding remark and some suggestions for further research are presented in the fifth part.

DATA AND VARIABLE

This study has analyzed the daily USD/TRY exchange rates for six months, from May to December 2022. The sample has been gathered from www.exchangerates.org.uk, which is a reliable database for financial time series. The data set has been divided into two sub-groups: the train and the test, with a ratio of 85–15 percent. This investigation has used the daily returns computed through the following formula:

$$Return_t = \frac{Rate_t - Rate_{t-1}}{Rate_{t-1}} * 100. \quad (1)$$

Generally, financial time series follow a random walk process, with a high level of variance. The mentioned transformation decreases the variance and pushes data toward a homoscedastic condition, making time series more suitable for further analyses by eliminating the possible unit root. Nevertheless, there is a high chance the return time series contains a unit or a fractional root.

The first step in data analysis is to compute the fundamental statistics, like the four primary moments and investigate if the data follow a specific distribution. However, before that, it would be beneficial to illustrate the data graph, which is plotted in *Fig. 1*.

It can be deduced from *Fig. 1* that the time series has a volatile nature. However, the volatility is more visible in the first third of the chart. Another clear thing is that there were two spikes during the first fifty observations. At first glance, they look like just two outliers, and it is highly predictable that the detection tests confirm it. In fact, if an outlier detection test is utilized, it would find more than just two points, which is unlikely in series with short time intervals. Furthermore, it is obvious the data has a skewed distribution; hence, assigning a normal distribution would not be realistic. Therefore, a high level of fluctuation in the time series trend, especially in the initial section, can be imputed to the non-linear nature of the series. In order to evaluate the mentioned analyses, descriptive statistics are reported in *Table 1*.

First, it should be mentioned that *J-B* is an abbreviation for the [16] normality test. Second, the *J-B* test shows the data does not follow a normal distribution. Third, as can be deduced from Table 1, the time series is left-skewed, in contrast to most financial time series that follow right-skewed distributions. On the other hand, skewness is an essential aspect of financial time series because it can be considered a measure of risk [17]. It is crucial because most econometric models like [18] or ARCH models of [19] assume the data follow normal or symmetric heavy-tailed distributions, which do not comply with this time series condition. However, there are many explanations for negative skewness. For instance, [20] discussed that a stochastic bubble could be the source of left skewness. Therefore, if the time series follows a bubbly regime, using equilibrium models like ARMA or almost all of the pricing theories like the Capital Asset Pricing Model or Arbitrage Pricing Theory, will lose their applicability. As a result, it can be claimed that a univariate model cannot describe all the time series fluctuations. To achieve a better understanding, a deep analysis of descriptive statistics will be needed. Since the time series mode is zero, discriminating data based on this criterion would be beneficial. *Table 2* provides an analysis according to the mode cut-off.

According to *Table 2*, investors on most days gained positive returns (but not necessarily excess returns). Moreover, the skewness can be easily described since the maximum duration of the period with continuous positive returns was higher than the negative one. Furthermore, the maximum number of days the time series was in an upward movement was equal to the number of days spent in a downward trend. Thus, it can be concluded that the effect of positive and negative shocks was similar, and hence, there is no leverage effect in the data. It is an important concept because, in the presence of the leverage effect, the data variance tends to behave conditionally, especially if the time series distribution is leptokurtic. To find more evidence, it can be beneficial to calculate the correlation coefficient between R_t^2 and R_{t-1} where R_t stands for the return time series. A negative value can be translated to a leverage effect; however, the estimated value is $Corr\left(R_t^2, R_{t-1}\right) = 0.1896$. Therefore, it can be said that there is no leverage effect.

For further analysis, another test known as the Runs test of [21], which analyzes the data distribution, can be employed. The null hypothesis states the time series follows an identically independent distribution; nevertheless, there is no specification under the alternative hypothesis. The rejection of the null implies the data does not follow a specific distribution but provides some evidence of unit roots as a stochastic time trend. If the data is not covariance stable, the mean and variance are time-dependent, and hence, the data cannot follow an identical independent distribution. It should be mentioned that the Runs test is nothing more than a necessary condition for stationarity. As a result, deciding on the stochastic time trend based only on the Runs test would lead to false conclusions. The outcomes of the test based on three thresholds are reported in *Table 3*.

Table 1

Descriptive Statistics

Statistic	Value
Mean	0.109
Median	0.055
Mode	0.000
Max	2.073
Min	−2.645
Std. Dev	0.436
Skewness	−0.321
Kurtosis	15.036
J-B Stat.	1083.451
J-B Prob.	0.000

Source: Research findings.

Since the time series length is more than 20 observations, the critical value has been extracted from the standardized normal distribution. As can be seen in *Table 3*, the null hypothesis has not been rejected for median and mode, while it has been rejected for mean threshold. So, it can be accounted for as a sign of a near-stationary process. That means the data does not follow a pure stationary process, but there is a mean-reverting behavior, and hence the effect of a shock decays at a rate slower than a completely stable process [22].

The next step is to determine if the time series contains any trends. Fortunately, there is a massive statistical literature about those tests; however, this paper has used two of the most well-cited unit root tests, including the augmented Dickey-Fuller (ADF) test of [23] and [24], known as the P-P test. The famous test of [25], known as the KPSS, has been employed to check if the series is stationary. The results of the tests are reported in *Table 4*.

The outcomes of *Table 4* have asserted that the time series neither has a unit root nor is stationary. This behavior could be a sign of a long-memory trend in time series, which is in the direction of the Runs test outcomes. However, for modeling purposes, the stationarity of the time series is an essential condition. Thus, to obtain a stable series, the data should be

Table 2

Frequency Discrimination

Value	No. of Days	Percent
Zero	16	8.94
Negative	48	26.81
Positive	115	64.25
Total	179	100
Max. days in negative returns		3
Max. days in positive returns		11
Max. days in an increasing trend		4
Max. days in a decreasing trend		4

Source: Research findings.

Table 3

Runs Test Outcomes

Threshold	Mean	Median	Mode
R	63	78	86
$\bar{R}$ (Exp.)	80.776	90.497	83.235
Std. Dev	5.942	6.670	6.126
Z-Stat.	−2.992	−1.873	0.451
Prob.	0.003	0.061	0.652

Source: Research findings.

subject to first-order differencing. The KPSS test results for the new time series are reported in *Table 5*.

As can be deduced from *Table 5*, the series has gotten stationary after differencing. As a neglected point, if there are structural breaks in the time series, the diagnostic power of stability tests will decrease exponentially. The first time, [26] showed that while the series has a unit root, the test rejected the null hypothesis in favor of the alternative. For this purpose, he added a dummy variable to the restricted model of the ADF test and did the test. He concluded that structural breaks increase type I errors in unit root tests. In this regard, it is vital to examine the time series for possible structural breaks. However, well-cited tests like [27] assume the breakpoint is known, which is not our case. To overcome that issue, [28, 29] suggested a test that does not need any prior information about the breakpoints. The test results are reported in *Table 6*.

The above results show the test statistic is less than the critical value; thus, the null of no breakpoint cannot be rejected. As a result, since there is no structural break, the outcomes of unit root/stability tests are reliable.

1. Modeling and Estimation

In almost all the univariate analyses, the autoregressive-moving average model, ARMA, is the first-line model for forecasting purposes. The model assumes the underlying process is linear and stationary. The general specification of an ARMA(p, q) model is as follows:

$$\varphi(L)Y_t = \theta(L)\varepsilon_t \quad s.t. \quad \varepsilon_t \sim WN\left(0,\sigma^2\right). \tag{2}$$

Where L is the lag operator in which $L(Y_t) = Y_{t-1}$ and ε_t are errors known as moving average components.

Table 4

Unit Root/Stationary Tests

ADF Test			
Null: There is a Unit Root.			
Sig. Level: 5%			
Type	**Statistic**	**Critical Value**	**Prob.**
Pure	−9.565	−1.943	0.000
Intercept and Trend	−10.356	−3.435	0.000
P–P Test			
Null: There is a Unit Root.			
Sig. Level: 5%			
Type	**Statistic**	**Critical Value**	**Prob.**
Pure	−9.537	−1.943	0.000
Intercept and Trend	−10.320	−3.435	0.000
KPSS Test			
Null: Time Series is Stationary			
Sig. Level: 5%			
Type	**L–M Stat.**	**Critical Value**	
Intercept	0.513	0.463	
Intercept and Trend	0.159	0.146	

Source: Research findings.

Both $\varphi(L)$ and $\theta(L)$ are two polynomials of L from the orders of p and q, respectively. If the absolute value of all the roots of the $\varphi(L)$ is greater than one, then the model is stationary. In other cases, the time series needs to get stable through the differentiation operator as follows:

$$\omega(L)(1-L)^d Y_t = \theta(L)\varepsilon_t \quad s.t. \quad (1-L)Y_t = \Delta Y_t = Y_t - Y_{t-1}. \quad (3)$$

And the parameter ***d*** is the number of differentiations needed to obtain a stationary process. In this case, the model is called ARIMA(p, d, q).

The first step in constructing an ARMA model is to decide on the number of lags. In this regard, taking advantage of the autocorrelation (ACF) and partial autocorrelation (PACF) functions would be beneficial. The graph of the functions is illustrated in *Fig. 2*.

As can be seen, there are two significant spikes in the ACF part, so it suggests an MA(2) process. In contrast, the PACF indicates significant jumps in lags one, two, four, and six. That means there are three possibilities for the autoregressive part, including AR(2), AR(4), and AR(6). However, for a better decision

Table 5

Stationary Test

KPSS Test		
Null: D (Return) Time Series is Stationary		
Sig. Level: 5%		
Type	L–M Stat.	Critical Value
Intercept	0.095	0.463
Intercept and Trend	0.087	0.146

Source: Research findings.

Table 6

Structural Breaks Test

Multiple Breakpoints Tests			
Bai-Perron Test of L vs. L+1 Sequentially Determined Breaks			
Breaking Variable: C (Level)			
Max Breaks: 5 Sig. Level: 0.05			
Covariance: Heteroscedastic-Autocorrelation Consistent (HAC)			
Break Test	F-Stat.	Scaled F-Stat.	Critical Value
0 vs. 1	3.563	3.563	8.580

Source: Research findings.

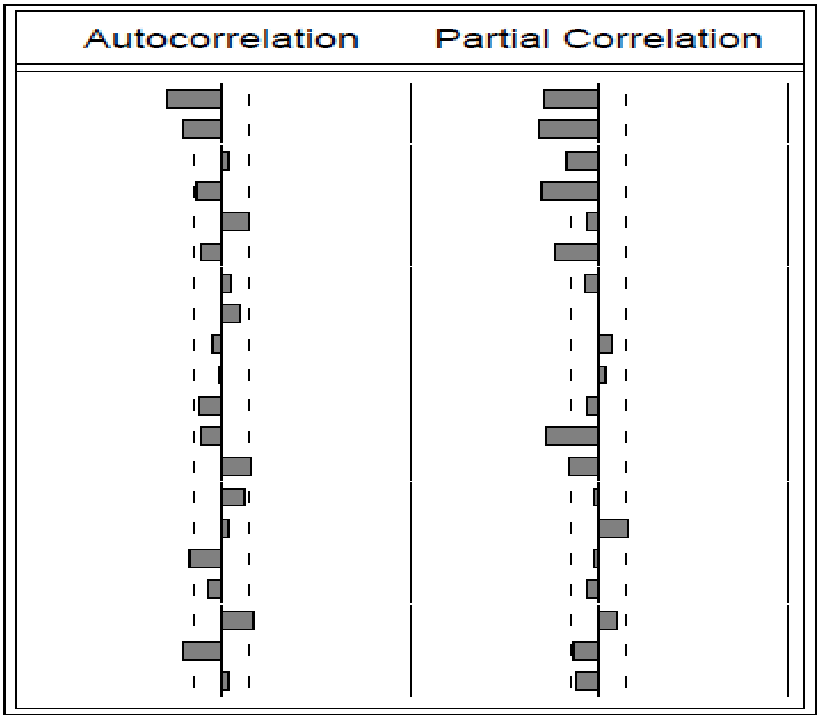

Fig. 2. **ACF and PACF of Differentiated Time Series**

Source: Research findings.

on the autoregressive component, taking advantage of information criteria would be helpful. The selected models concerning the criteria are reported in *Table 7*.

According to *Table 7*, all the criteria indicate the moving average part should contain two lags, as has been confirmed by the ACF plot. However, there is no unique agreement about the autoregressive element. On the other hand, among the criteria, only the BIC has offered lags similar to the PACF function. It was not a surprising outcome because, as a general rule, the Bayesian criterion is more suitable for small samples [30]. As a result, two lags have been picked for the autoregressive component. The estimated model is reported in *Table 8*.

Unfortunately, the estimation has come with disappointing results both in explanatory power and residual diagnosis. First, except for the AR (1), all the coefficients were statistically insignificant. Moreover, the adjusted R-squared statistic is around 39 percent. The worst part was residual diagnostic test outcomes because they displayed error terms that had not been distributed normally. However, the ARCH effect has

Table 7

Model Selection

Model: ARMA (P, Q) $s.t. \quad P, Q \epsilon [1,7]$ Variable: D (Returns) Estimating Technique: Maximum Likelihood (Normal Distribution)		
Criterion	**Value**	**Suggestion**
AIC	1.097	ARMA(7, 2)
BIC	1.205	ARMA(2, 2)
H-Q	1.159	ARMA(1, 2)

Source: Research findings.

Table 8

Estimated ARIMA Model

Estimated Model: ARIMA(2, 1, 2) Estimating Method: Maximum Likelihood (Normal Distribution)				
Variable	**Coef.**	**Std. Err.**	**t-Stat.**	**Prob.**
C	–0.002	0.002	–0.913	0.362
AR(1)	–0.534	0.140	–3.807	0.000
AR(2)	0.092	0.083	1.101	0.272
MA(1)	–0.152	141.724	–0.001	0.999
MA(2)	–0.848	1030.836	–0.001	0.999
R-Sq	0.401			
Adj. R-Sq	0.384		AIC	1.128
F-Stat.	23.079		BIC	1.205
F-Prob.	0.000		H-Q	1.171
Normality Test				
J-B Stat.	1397.033			
J-B Prob.	0.000			
Heteroscedasticity Test: ARCH				
F-Stat.	1.335	Prob. F(1, 175)	0.249	
Lagrange-Stat.	1.340	Prob. Chi-Sq(1)	0.247	

Source: Research findings.

been rejected, and thus, the residuals are homoscedastic. Also, another part that has not been reported in Table 8 is the serial correlation test. For this purpose, the Q-statistic of [31] for lags from five to ten has been analyzed. Since the estimated parameters $(P+Q=4)$ have restricted the degrees of freedom, the test has to start from the fifth lag. The outcomes are reported in *Table 9*.

The results reported in *Table 9* show there is no autocorrelation in the residuals' time series. As stated earlier, the tests in *Table 8* rejected the ARCH effect as a kind of heteroscedasticity. As a result, there is no reason to estimate a GARCH model. The last family of models that will be discussed is known as the exponential smoothing models, which were first introduced by [32]. The models (Known as Brown's

Table 9

Ljung-Box Test

Variable: ARIMA(2, 1, 2) Residuals		
Null: There is no Serial Correlation. Sig. Level: 0.05		
Lag	**Q-Stat.**	**Prob.**
5	2.245	0.134
6	2.248	0.325
7	3.078	0.380
8	4.728	0.316
9	5.578	0.350
10	7.647	0.265

Source: Research findings.

models) assume the closer data has more influence on the overall trend than the distant data. Suppose $\{Y_t\}_1^N$ is a time series and the exponentially smooth filtered values are denoted by $\hat{Y}_t$. Also, consider an adjusting parameter $0 \le \alpha \le 1$ where it controls the weighting procedure. Moreover, suppose there is no deterministic time trend and seasonality. Therefore, the filtering process is as follows:

$$\hat{Y}_t = \alpha Y_t + (1-\alpha)\hat{Y}_{t-1} \quad s.t. \quad \hat{Y}_1 = Y_1. \tag{4}$$

Hence, for the forecasting purposes, $Y_{t+h|t} = \hat{Y}_t$.

[33] extended Brown's model by adding a linear trend in the time series (known as Holt's model), and rewrite the equations as follows by introducing a new parameter $\beta \in [0,1]$.

$$\hat{Y}_t = \alpha Y_t + (1-\alpha)\left(\hat{Y}_{t-1} + \Delta\hat{Y}_{t-1}\right) \quad s.t. \quad \hat{Y}_1 = Y_1,$$

$$\Delta\hat{Y}_t = \beta\left(\hat{Y}_t - \hat{Y}_{t-1}\right) +$$
$$+(1-\beta)\Delta\hat{Y}_{t-1} \quad s.t. \quad \Delta\hat{Y}_2 = Y_2 - Y_1. \tag{5}$$

Where similar to Brown's model, α is the smoothing parameter for the level factor and β is the smoothing parameter for the trend. Forecasting in this framework is quite simple using the below equation:

$$Y_{t+h|t} = \hat{Y}_t + h.\Delta\hat{Y}_t \tag{6}$$

It should be mentioned if $\beta = 0$, Holt's model reduces to Brown's specification. There are two approaches to determining control parameters, including assigning values to the data prior to the calculation or using goodness-of-fit criteria like root mean squared error (RMSE) or mean absolute error (MAE). For instance, [34] suggested an $\alpha \in [0.1, 0.3]$ would be a suitable choice, however, [35] discussed in favor of a parameter on the interval of $[0.05, 0.5]$. In contrast, [36] stated that using forecasting evaluation criteria could provide better model tuning compared to assigning prior beliefs on the parameters. Nevertheless, in order to avoid any possible bias, this study has used the RMSE criterion. The estimated elements of Holt's and Brown's models are reported in *Table 10*.

As can be seen, the beta parameter in Holt's model is zero, and hence, there is no deterministic trend. Therefore, the method is equivalent to Brown's technique. Accordingly, only Brown's exponential smoothing method will be employed. The interesting point about the estimated parameters is that although the beta is zero, and so, by definition, two models should be equivalent, the estimated alphas are different. The reason behind this disagreement is that a beta equal to zero reduces the value of $\Delta\hat{Y}_{t-1}$ to

Table 10

Exponential Smoothing Estimation

Variable: Returns				
No. of Observations: 179				
Model	**Alpha (α)**	**Beta (β)**	**Sum Sq-Resid.**	**RMSE**
Holt	0.160	0.000	35.475	0.445
Brown	0.026	–	33.619	0.433

Source: Research findings.

$\Delta\widehat{Y}_2 = Y_2 - Y_1$, but in the time series under investigation, $Y_2 \neq Y_1$; therefore, the two models are not completely equal. However, since the beta is zero, the estimated alpha for Holt's model should be neglected.

There are several concerns regarding the estimated models. First, none of the estimated models have provided normally distributed residuals. This phenomenon can be related to some omitted variables or model misspecification. Second, all models' explanatory power (adjusted R-square statistic) was less than fifty percent. Consequently, the estimated models have no ability to explain all the underlying reasons behind the fluctuating behavior of the time series. In summary, the estimated models of this study should only be applied for short-term forecasting purposes.

2. Forecasting and Discussion

As discussed earlier, the ARIMA (2, 1, 2) has been selected as the most suitable model. However, as suggested by the PACF plot, two other lags, including four and six, could also be picked as the autoregressive part. Hence, ARIMA (4, 1, 2) and ARIMA (6, 1, 2) also be used in the forecasting stage. To widen this domain, four other models, including MA (2), AR(2), AR(4), and AR(6), have been added to the models' collection. Furthermore, as a tradition in financial time series forecasting, the random walk model, which is the symbol of the efficient market hypothesis (EMH), has been employed in order to be the benchmark model. While this hypothesis has been subjected to several criticisms,[3] it is still considered a suitable model for comparison purposes. In fact, forecasting through this model is quite simple, and for this reason, it is called the naïve forecasting procedure. In this algorithm, all the approximated future data are equal to the last observation. Mathematically speaking,

$$\widehat{Y}_{t+h|t} = Y_t \quad where \quad h = 1, 2, \ldots \tag{7}$$

The equation holds because:

$$\begin{gathered} Y_t = Y_{t-1} + \varepsilon_t \quad s.t. \quad \varepsilon_t \sim WN\left(0, \sigma^2\right) \\ \to \; E\left(Y_t \,|\, Y_{t-1}\right) = \\ = E\left(Y_{t-1} \,|\, Y_{t-1}\right) + E\left(\,_t\right) \to \; E\left(Y_t \,|\, Y_{t-1}\right) = Y_{t-1}. \end{gathered} \tag{8}$$

Another simple forecasting model is the mean indicator. The model is almost similar to the naïve forecast, but the last observation should be replaced with the sample mean. Roughly speaking, all the future values equal the time series expected value. Thus,

$$\widehat{Y}_{t+h|t} = E(Y_t) \quad where \quad h = 1, 2, \ldots \tag{9}$$

The last model is exponential smoothing, and according to the previous section, only Brown's model will be used.

This study has employed three evaluating criteria, including RMSE, MAE, and the symmetric Mean Absolute Percentage Error (SMAPE). All three indices calculate as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(\widehat{Y}_i - Y_i\right)^2}{n}}, \tag{10}$$

$$SMAPE = \frac{\sum_{i=1}^{n} \frac{|\widehat{Y}_i - Y_i|}{|\widehat{Y}_i| + |Y_i|}}{n} * 200, \tag{11}$$

[3] For instance [37] by estimating the Hurst exponent in a rolling-windows procedure, rejected a random walk hypothesis in favor of a fractal one in the Warsaw stock exchange.

Table 11

Forecasting Evaluation

Model	RMSE	MAE	SMAPE
ARIMA(2, 1, 2)	0.218	0.154	158.847
ARIMA(4, 1, 2)	0.221	0.156	159.427
ARIMA(6, 1, 2)	0.228	0.156	154.586
AR(2)	0.209	0.147	156.286
AR(4)	0.221	0.155	159.103
AR(6)	0.231	0.158	162.342
MA(2)	0.218	0.153	157.511
Random Walk	0.217	0.144	140.263*
Mean Index	0.226	0.157	141.562
Brown's Smoothing	0.205*	0.123*	147.414

Source: Research findings.

Note: * indicates the best model.

$$MAE = \frac{\sum_{i=1}^{n} |\hat{Y}_i - Y_i|}{n}.$$

By definition, all the criteria are non-negative, and a value equal to zero means a fully matched forecast. As a result, values closer to zero indicate better forecasting performance. However, since RMSE uses a square operator, it is more sensitive to outliers compared to MAE. On the other hand, if both the actual value and the forecasted one are too close to zero, the symmetric MAPE could be undefined. Thus, the MAE is the study's preferred criterion.

The test group for the out-of-sample forecast contained 33 observations, and the model forecasting evaluation is reported in *Table 11*.

Table 11 clearly shows no agreement among criteria in selecting the best forecasting model. However, two out of three criteria have selected the simple exponentially weighted method. It should be mentioned that the naive forecast is the second-best model, and this finding confirms that a random walk model should always be among the forecasting techniques.

The outcomes asserted that the ARIMA models exhibited poor performance in the forecasting step. But it could be attributed to the fact that the time series has displayed some evidence of long-term memory behavior, which complies with [7] conclusion. On the other hand, the lack of heteroscedasticity contradicts the findings of [10]. Finally, the weakness of autoregressive models in the prediction stage is contrary to the argument in paper [9].

CONCLUSION

Forecasting financial time series has always been a desired task for all market agents, especially risk-taker investors. Forecasting makes investors capable of seeing beyond the uncertainty surrounding future trends and thus taking advantage of numerous opportunities. Among all the financial time series, exchange rates have a unique place because they are not only considered a vital parameter in monetary policies but highly correlated with the citizens' daily lives. A sharp decline in national currency decreases purchasing power by increasing the prices of imported goods and services. Moreover, its inflationary effects do not restrict to imported commodities because it causes foreign trade imbalance and eventually pushes living standards toward lower levels.

Turkey always has a unique position among its neighbors due to its situation as a bi- continental country and the fact that it is one of the safest transit channels between Europe and Western Asia. As a result, the country plays a crucial role in regional and international economics. Nevertheless, during the past year, the Turkish lira exchange rate has been subjected to severe fluctuations and caused several inflationary waves. In fact, multiple reasons, including the increase in the world's inflation levels due to Russia's invasion of Ukraine or economic recession of the COVID-19 pandemic, can be considered triggers for such a variable trend. However, among all the nominated explanations, the Turkish central bank policy to decline interest rates has the most influence. However, ss much as volatility in exchange rates could be harmful to macroeconomics, it provides a golden opportunity for some investors to take advantage of the arbitrage opportunities. The subject got more interesting when, in the absence of inflation-indexed government bonds, new amateur investors entered the market with the desire to hedge their savings against the upcoming inflationary waves. In this regard, the present study has employed several univariate models to provide reliable forecasting using the USD/TRY daily time series. For this purpose, the linear models of Box-Jenkins and exponentially weighted smoothing techniques have been utilized. Although the time series exhibited left-skewed leptokurtic distribution, the ARCH and leverage effects have been rejected.

In the modeling step, seven ARIMA models and two types of smoothing filters have been estimated. Since the trend parameter in Holt's method was zero, only Brown's smoothing filter with an alpha near zero has been used. Furthermore, to provide a benchmark among the competitive models, this study took advantage of a pure random walk model, well-known as a naive forecasting procedure. The forecasting evaluation revealed that Brown's method provided the best predictions; however, the second-best place was allocated to the naive model. As a result, the study concluded that the simple models can outperform the sophisticated ones and the traditional forecasting models still have some levels of applicability. In this regard, it suggests that amateur investors in the exchange market should at least use long-established techniques like a random walk model.

During the modeling process, the unit root and stationary tests showed the time series has some characteristics of a long-memory process. Future studies should focus on this feature and determine if the behavior is a true mean-reverting process or just got mistaken with a more complex model of Markov regime switching.

Declarations

- The data that supports the study findings is available freely and publicly at https://www.exchangerates.org.uk/USD-TRY-exchange-rate-history.html
- The authors declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.
- This research did not receive any financial aid from government, private, or not-for-profit agencies.

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