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Modelling of the Weighted Average Funding Cost of the CBRT: LNV-ARMA Approach

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TCMB Ağırlıklı Ortalama Fonlama Maliyetinin Modellenmesi: LNV-ARMA Yaklaşımı

Abstract

In this study, we model the monthly time series of the Central Bank of the Republic of Turkey's Weighted Average Funding Cost (Interest Rate) for the period between 2011:01-2020:12. In this framework, we establish and compare the linear and the nonlinear based various autoregressive (integrated) moving average models in two separate groups and investigate the most suitable model for the series. After all, we reveal that the relevant interest rate series can be modelled best with the LNV-ARMA(2,1) model for the related period. The first novelty of this study is that we model the relevant interest rate itself instead of investigating the relationship of this interest rate with the other macroeconomic variables. The second novelty of this study is that we circumvent the unit root problem and establish a more explanatory time series model by applying the LNV methodology.

Keywords : CBRT WAFC, LNV Methodology, ARIMA Models, Time Series, Turkey.

JEL Classification Codes : C22, C24, C52, E43, E47, E58.

Öz

Bu çalışmada, 2011:01-2020:12 dönemine ait Türkiye Cumhuriyet Merkez Bankası Ağırlıklı Ortalama Fonlama Maliyeti (Faiz Oranı) aylık zaman serisi modellenmiştir. Bu çerçevede, iki ayrı grupta doğrusal ve doğrusal olmayan temelli çeşitli otoregresif (bütünleşik) hareketli ortalama modelleri kurularak karşılaştırılmış ve seriye en uygun model araştırılmıştır. Sonuç olarak, ilgili faiz oranı serisinin bahsi geçen dönem için en iyi LNV-ARMA(2,1) modeli ile modellenebileceği ortaya konmuştur. Bu çalışmanın ilk yeniliği, bu faiz oranının diğer makroekonomik değişkenlerle ilişkisini araştırmak yerine ilgili faiz oranının kendisini modellememizdir. Bu çalışmanın ikinci yeniliği, LNV metodolojisini uygulayarak birim kök sorununu aşmamız ve daha açıklayıcı bir zaman serisi modeli oluşturmamızdır.

Anahtar Sözcükler : TCMB AOFM, LNV Metodolojisi, ARIMA Modelleri, Zaman Serileri, Türkiye.

1. Introduction

The Central Bank of the Republic of Turkey's (CBRT) Weighted Average Funding Cost (WAFC) or Interest Rate (WAFR) is defined as the weighted average of the overnight, weekly, etc. funding interest rates, which are made by using various instruments such as repo by the CBRT to meet the short-run liquidity need in the market (CBRT, 2021). Since this funding made by the CBRT constitutes a significant part of the short-term liquidity provided by the banks, this interest rate may be crucial for the banks in pricing the deposits, loans, and other financial instruments (Kara, 2015).

There are many empirical studies in the literature on the CBRT WAFC. These are generally designed to investigate the relationship between the CBRT WAFC and various macroeconomic variables (e.g., Ekinci et al., 2016; Küçük et al., 2016; Tunalı & Yalçınkaya, 2017; Varlık & Berument, 2017; Güler & Özçalık, 2018; Binici et al., 2019; Büberkökü & Kızılder, 2019; Sümer, 2019; Yüksel et al., 2019; Kartal, 2020; Felek & Ceylan, 2021). Unlike these studies, we model the CBRT WAFC time series based on the monthly data for the period between 2011:01-2020:12 in the framework of autoregressive (integrated) moving average [AR(I)MA] models by using two different approaches with linear and nonlinear and investigate comparatively. In this way, we aim to give ideas to the market participants, especially banks, by revealing to what extent the current value of the relevant time series is affected by the previous values of the series and to what extent by the random shocks. The first contribution of this study is that we model the relevant interest rate itself instead of investigating the relationship of this interest rate with the other macroeconomic variables.

We consider modelling the CBRT WAFC time series with the linear and the nonlinear approaches to make it stationary. We eliminate the stochastic and deterministic trends in the series by using difference stationarity and trend stationarity methods. In this context, we use the linear ADF unit root test and the nonlinear unit root test developed by Leybourne et al. (1998) [LNV]. The second contribution of this study is that we circumvent the unit root problem and establish a more explanatory time series model by applying the LNV methodology.

There are two motives why we prefer the LNV test in this study. Firstly, this test is one of the unit root tests, which includes a break in mean and/or trend. Unlike the unit root tests proposed by Perron (1989; 1990; 1997), Rappoport and Reichlin (1989), Zivot and Andrews (1992), and Lumsdaine and Papell (1997), which the assumption of instant deterministic structural change in mean and/or trend is made, the LNV unit root test, which has a smooth transition regression (STR) based model, allows gradual adjustment between the two regimes. This is more suitable for the structure of the economic time series. Because it is improbable for all economic agents to react simultaneously to an economic stimulus. Secondly, this test enables the detection and elimination of nonlinear structures, which may cause unit root problems in variables.

The remainder of the study is structured as follows: In Part 2, we present various empirical studies in the literature on the CBRT WAFC. In Part 3, we explain the empirical methodology applied in this study. In Part 4, we deal with the data and the unit root test results and make a comparative analysis by establishing various models in two different groups. The last part consists of the concluding remarks.

2. Literature Review

There are various empirical studies in the literature on the CBRT WAFC. We briefly explain some of these studies below.

Ekinci et al. (2016) investigate whether the CBRT WAFC is effective on the Borsa Istanbul (BIST) 100 index and conclude that the CBRT WAFC does not affect the BIST 100 index. Küçük et al. (2016) empirically analyse what determines the overnight spread between the Borsa Istanbul (BIST) repo rate and the CBRT average funding rate and find that it is recently affected by many factors both directly and closely related to the CBRT's liquidity policy. Varlık and Berument (2017) examine the effects of different monetary policy interest rates for a central bank on economic performance and indicate that choosing different policy rates allows the CBRT to achieve differentiated economic results. The finding specific to the CBRT's average funding rate is that this policy interest rate is more effective on the Treasury bond interest rates, the consumer credit interest rates, time deposits, and portfolio investments than the other monetary policy rates. Tunalı and Yalçınkaya (2017) analyse the relationship between the dollar rate, the inflation rate, and the CBRT WAFC and reveal bi-directional causality between the CBRT WAFC and the dollar rate. Güler and Özçalık (2018) examine the relationship between the BIST 100 index, the CBRT WAFC, the dollar index, and the dollar/TL rate and find that all variables are affected by each other. Binici et al. (2019) investigate the relationship between the short-term official & effective interest rates and the bank loan & deposit interest rates. The findings show that the bank loan & deposit interest rates are more sensitive to the effective interest rates like the CBRT average funding rate than the official interest rates like the CBRT lending rate. Yüksel et al. (2019) investigate whether the interest rate policy carried out by the CBRT affects the exchange rate. The findings related to the variables of the CBRT benchmark interest rate, the CBRT WAFC, and the dollar rate show that the interest rate policy is effective on the exchange rate; however, this relationship is not in the dimension of causality. Sümer (2019) analyses the overshooting effect of unconventional monetary policy shocks in Turkey. The findings in the study using the CBRT WAFC, the FED federal funds rate, and the dollar rate variables show that unconventional monetary policy shocks don’t have an overshooting effect in Turkey. Büberkökü and Kızılder (2019) examine the effect of the CBRT's unconventional monetary policy on the market interest rates. The findings in the study using the CBRT WAFC and the Borsa Istanbul overnight interest rates (BIST O/N) to represent the policy stance of the Central Bank show that there is a long-term relationship between the CBRT WAFC & the Borsa Istanbul overnight rates and the market interest rates (*the weighted average interest rates of the vehicle and commercial loans extended by the banks and the weighted average interest rates applied to the deposits with various maturities* *opened by the banks*). In addition, the findings reveal that the CBRT WAFC has a more considerable effect on the bank loan and deposit interest rates than the Borsa Istanbul overnight rates. The complete pass-through is only between the CBRT WAFC and the vehicle & the commercial loans. Kartal (2020) investigates the effects on the key financial indicators of the monetary policy measures taken in Turkey during the Covid-19 pandemic. The findings reveal that during the pandemic period, there are causality relationships from the weighted average funding cost and the size of the securities purchased by the Central Bank to the US dollar rate. Felek and Ceylan (2021) investigate whether the Neo-Fisher theory is valid in the interest-inflation interaction in Turkey. The findings reveal causality relationships from all interest rate variables (including the CBRT WAFC) implemented in the study to the inflation, but not the other way round. Therefore, they conclude that the Neo-Fisher theory is valid in Turkey.

As can be seen, the literature mostly deals with the relationship between the CBRT WAFC and various macroeconomic variables. This study aims to model the related interest rate's possible linear and nonlinear structure and reveal its internal dynamics. In this way, we can make various policy implications over the set of information in the data.

3. Empirical Methodology

3.1. Stationarity & Unit Root Tests

Stationarity is the absence of a systematic change in a time series's mean and variance, besides not revealing regular periodic changes. The concept of stationarity in time series can be seen in different ways. In the time path graph of a time series, the situation where there is no change in the mean overtime is defined as mean stationarity, and the situation where there is no change in the variance overtime is defined as variance stationarity. While the concept of difference stationarity is defined as making stationary of a time series by removing the stochastic trend it has, on the other hand, the concept of trend stationarity is defined as making stationary of a time series by getting rid of the deterministic trend it has. In the application related to making stationary of time series, we encounter two basic processes: trend stationarity and difference stationarity. The principal separation between the trend stationary process and difference stationary process relates to the duration of the impact of short-term shocks (for example, shocks from policy change) on the series. In the case of trend stationarity, the short-term shocks influence the long-term development of the series temporarily, while in the case of difference stationarity, the short-term shocks influence the level of the series continuously (Sevüktekin & Çınar, 2014: 81, 239-247).

The stationarity of a time series can be examined through unit root tests. These tests can be broadly categorised under three headings. These titles are; (i) Standard linear unit root tests (e.g., Dickey & Fuller, 1979; Phillips & Perron, 1988 [PP]; Kwiatkowski et al., 1992 [KPSS]; Phillips & Ploberger, 1994; Elliott et al., 1996; Perron & Ng, 1996; Bierens, 1997; Im et al., 2003), (ii) Unit root tests employing a nonlinear model (e.g., Enders & Granger, 1998 [EG]; Sollis et al., 2002; Kapetanios et al., 2003 [KSS]; Sollis, 2009) and (iii)

Unit root tests including a break in the mean and/or trend (e.g., Perron, 1989;1990;1997; Rappoport & Reichlin, 1989; Zivot & Andrews, 1992; Lumsdaine & Papell, 1997; Leybourne et al., 1998 [LNV]; Sollis et al., 1999; Becker et al., 2006; Vougas, 2006) (Omay, 2012).

3.2. LNV Methodology

For a y_t time series, Leybourne et al. (1998) [LNV] propose the following three logistic smooth transition regression (L-STR) models:

Model K $y_t = \alpha_1 + \alpha_2 G_t(\gamma,\tau) + v_t$ (1)

Model L $y_t = \alpha_1 + \beta_1 t + \alpha_2 G_t(\gamma,\tau) + v_t$ (2)

Model M $y_t = \alpha_1 + \beta_1 t + \alpha_2 G_t(\gamma,\tau) + \beta_2 t G_t(\gamma,\tau) + v_t$ (3)

where v_t is a zero-mean I(0) process, $G_t(\gamma,\tau)$ is a logistic smooth transition function representing the transition between the regimes. This function is defined as follows:

$$G_t(\gamma,\tau) = [1 + exp\{-\gamma(t - \tau T)\}]^{-1}, \gamma > 0 \quad (4)$$

where T is the number of observations (sample size), t is the time trend considered as the transition variable in the transition function, γ is the transition speed between the regimes, and τ is the midpoint of the transition (threshold-location parameter). The transition between the regimes is not in a sudden structural break form but gradual. The transition function $G_t(\gamma,\tau)$ is a continuous and monotonous function ranging from 0 to 1. Therefore, the STR models considered in Equations (1), (2), and (3) can be interpreted as regime-switching models with two extreme regimes (Omay & Yıldırım, 2013). While the extreme values of the transition functions are $G_t(\gamma,\tau) = 0$ and $G_t(\gamma,\tau) = 1$, the transition from one extreme regime to the other takes place gradually. The transition path is symmetrical around the midpoint. If the value of γ in the function is small, $G_t(\gamma,\tau)$ travels in the interval (0,1) for a long time. If γ is 0, then the $G_t(\gamma,\tau)$ function takes the value 0.5 for all t's. For large values of γ, $G_t(\gamma,\tau)$ travels very quickly in the interval (0,1). As γ goes to $+\infty$, the function changes value from 0 to 1 abruptly in a moment of $t = \tau T$.

On the assumption that v_t is a zero-mean I(0) process, in Model K, the y_t time series is stationary around a varying mean from the first value α_1 to the ultimate value $\alpha_1 + \alpha_2$. In Model L, in addition to the process in Model K, the constant slope parameter (β_1) is also considered. In Model M, on the other hand, with the change in the intercept term from α_1 to $\alpha_1 + \alpha_2$, a simultaneous change is allowed in the slope from β_1 to $\beta_1 + \beta_2$ at the same transition speed.

LNV propose that the establishment of unit root hypotheses and the calculation of test statistics should be done as follows:

H_0 : Linear Non-Stationarity ($y_t = \mu_t$, $\mu_t = \mu_{t-1} + \varepsilon_t$)

H_1 : Nonlinear Stationarity (*Model K, Model L, or Model M*)

where ε_t is assumed to be a zero-mean stationary process [i.e., I(0)]. The proposed test statistics are computed by a two-stage method. In Stage 1, the deterministic component of the preferred model is estimated employing the nonlinear least squares (NLS) method, and then the residuals are calculated as shown in Equations (5), (6), and (7).

$$\text{Model K } \hat{v}_t = y_t - \hat{\alpha}_1 - \hat{\alpha}_2 G_t(\hat{\gamma}, \hat{\tau}) \tag{5}$$

$$\text{Model L } \hat{v}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 G_t(\hat{\gamma}, \hat{\tau}) \tag{6}$$

$$\text{Model M } \hat{v}_t = y_t - \hat{\alpha}_1 - \hat{\beta}_1 t - \hat{\alpha}_2 G_t(\hat{\gamma}, \hat{\tau}) - \hat{\beta}_2 t G_t(\hat{\gamma}, \hat{\tau}) \tag{7}$$

In Stage 2, $\hat{v}_t$ is modelled as in Equation (8). Afterwards, the null hypothesis of $\hat{\rho} = 0$ is tested using ADF test statistics.

$$\Delta\hat{v}_t = \hat{\rho}\hat{v}_{t-1} + \sum_{i=1}^{k} \hat{\delta}_i \Delta\hat{v}_{t-i} + \hat{\eta}_t \tag{8}$$

The ADF test statistics of LNV are named as s_α, $s_{\alpha(\beta)}$, and $s_{\alpha\beta}$ according to the model used to construct $\hat{v}_t$. Particularly, it is s_α if Model K is used, $s_{\alpha(\beta)}$ if Model L is used, and $s_{\alpha\beta}$ if Model M is used. The critical values of these test statistics are gained thanks to Monte Carlo simulations in the LNV approach (Leybourne et al., 1998).

3.3. ARIMA Models

For a Y_t time series, an autoregressive integrated moving average [ARIMA (p, d, q)] model can be expressed in polynomial form as in Equation (9):

$$\Phi(L)(1-L)^d(Y_t - \mu_t) = \Theta(L)\varepsilon_t \tag{9}$$

where L is the lag operator, $\Phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$ and $\Theta(L) = 1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$ denote lag polynomials, d is the integer order of differencing to be applied to the series, μ_t is the intercept and ε_t is the error term.

The methodology proposed by Box and Jenkins (1976) [Box-Jenkins] is prevalently used to establish a time series model. This approach is accepted as the method of finding the most appropriate ARIMA data generation process (DGP) for the actual data. The main steps of the related approach can be discussed in four stages in general terms: (i) Determination (identification) of the time series model, (ii) Making parameter estimations, (iii) Checking the adequacy of the model using diagnostic tests, and (iv) Using the model for forecasting. Notwithstanding, some matters must be considered to determine the model best fits a time series. These can be listed as the estimated parameters being significant, the residual sum of squares (RSS) being small, the likelihood ratio (LR) being as high as possible, the coefficient of determination (R^2), or the adjusted coefficient of determination ($\bar{R}^2$) being high, the F-statistics of the model being significant, the Akaike and the Schwarz information criteria

(AIC and SIC) being small, and the Portmanteau tests, or the Q-statistics calculated for the error terms of the model being insignificant (Sevüktekin & Çınar, 2014: 188-214).

4. Data and Empirical Analysis

4.1. Data and Unit Root Tests Results

This study uses monthly data from 120 observations between 2011:01-2020:12 for the CBRT Weighted Average Funding Cost (WAFC). The relevant data is acquired from the CBRT Electronic Data Distribution System (EDDS). The possible seasonality analysis of the monthly series is made by using the Tramo/Seats method, but it's not found any seasonality finding.

To model the CBRT WAFC time series, firstly, we carry out the stationarity analysis. For this, we employ a nonlinear test developed by LNV, one of the unit root tests with a break in the mean and/or trend, together with the linear and widely used ADF unit root test. The ADF test results are shown in Table 1.

Table: 1
ADF Unit Root Test Results

Variable	Model without Intercept and Trend	Model with Intercept, without Trend	Model with Intercept and Trend
$WAFC$	-0.387517 (0.5425)	-2.237531 (0.1944)	-3.589010 (0.0351)
$D-WAFC$	-3.142790 (0.0019)	-3.172292 (0.0242)	-3.141715 (0.1017)
$DD-WAFC$	-14.36914 (0.0000)	-14.31848 (0.0000)	-14.28712 (0.0000)

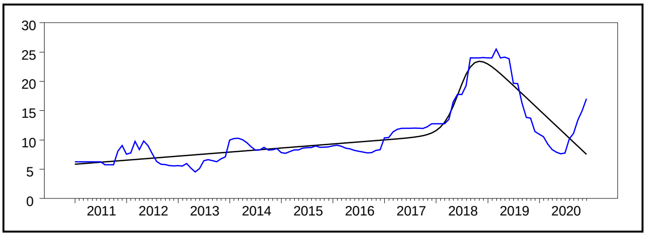
Note: The figures are t-statistics and p-values (in parenthesis).

In Table 1, *WAFC* shows the level value of the variable, *D-WAFC* shows the first difference of the variable, and *DD-WAFC* shows the second difference of the variable. When the ADF results for the level value of the variable are examined, we see that only the model with intercept and trend is significant at 5%, hence stationary. However, when the first difference of the variable is taken, we see that the model with intercept and trend is not significant even at 10%, that is, not stationary. However, we see that the model without intercept and trend and the model with intercept without trend are significant at 1% and 5%, respectively, that is, stationary. When the second difference of the variable is taken, there is significance at 1% for all three model types, therefore stationarity.

Then, we investigate the possible deterministic trend in the series using Model M [Equation (3)] of the LNV methodology, which considers the structural break and is explained in detail above. The unit root test is carried out employing the residuals acquired from Model M, and the t-statistics value ($s_{\alpha\beta}$) is calculated as 19.4924. Since this value is bigger than the absolute values of the critical values given in the LNV methodology (-5.650, -5.011, and -4.697, respectively) at 1%, 5%, and 10%, the unit root hypothesis is rejected, and the alternative one, nonlinear stationarity, is accepted. As can be seen in Figure 1, the WAFC series has a nonlinear deterministic trend structure. Removing this structure from the WAFC series makes it stationary (trend stationarity). The stationary WAFC series and the

ADF test results of the WAFC series before and after stationarity are shown in Figure 2 and Table 2, respectively.

Figure: 1
WAFC and Nonlinear Deterministic Trend



WAFC *Nonlinear Deterministic Trend.*

Figure: 2
Trend Stationary WAFC

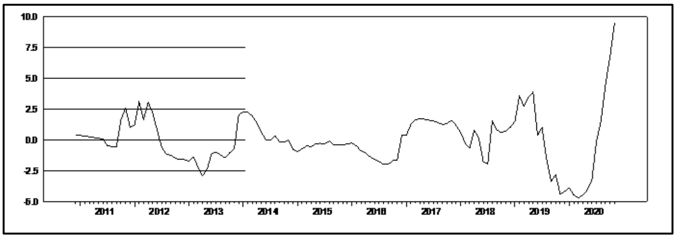


Table: 2
ADF Unit Root Test Results Before and After Trend Stationarity

Variable	Model without Intercept and Trend	Model with Intercept, without Trend	Model with Intercept and Trend
$WAFC$	-0.387517 (0.5425)	-2.237531 (0.1944)	-3.589010 (0.0351)
$LNV-WAFC$	-3.749357 (0.0002)	-3.683628 (0.0055)	-3.516998 (0.0422)

Note: The figures are t-statistics and p-values (in parenthesis).

In Table 2, *WAFC* represents the original level value of the variable, and *LNV-WAFC* represents the trend stationary *WAFC* series. When both series are compared, unlike the difference stationary series, we can say there is no observation loss. In the *LNV-WAFC* series, the nonlinear trend structure is removed from the original series, and thus the series is made stationary. When the ADF test results are examined, we can see that the original level value of the variable is significant (stationary) according to the 5% significance level only in the model with intercept and trend and insignificant (non-stationary) in the others. However, in the ADF analysis performed over the series that made trend stationary (*LNV-WAFC*) using the LNV methodology, we can see that the model without intercept and trend and the model with intercept without trend are significant (stationary) at 1%, in addition to the model with intercept and trend is significant (stationary) at 5%.

The results acquired from the unit root tests demonstrate that *LNV-WAFC* and *DD-WAFC* variables can be used in the model setup. Therefore, in the next section, LNV-ARMA and ARIMA models will be constructed and compared using these two variables as dependent variables.

4.2. Models and Comparative Analysis

Since the basic idea of the Box-Jenkins approach, which is widely used in establishing the ARIMA models, is based on the principle of parsimony, this principle envisages the establishment of an optimal model that reveals the characteristics of time series data. Here, optimal means having a minimum number of parameters in the model or considering the degrees of freedom. Box and Jenkins (1976) argue that the frugal models produce better predictions than the models with excessive parameters. Therefore, in this study, we establish various ARIMA models in line with the relevant principle and make the model selections by considering the Akaike Information Criteria (AIC) among the converged models. This criterion measures the model's goodness of fit by the number of terms in the model. While the AIC can generally be used to select the model that fits well among the alternative multivariate models, it can also be used to define the appropriate model degree for ARIMA models (Sevüktekin & Çınar, 2014:188,199). Models with different AR and MA components are shown in Table 3.

Table: 3
LNV-ARMA and ARIMA Models

LNV-ARMA Models	AIC Values	ARIMA Models	AIC Values
(2,1)	2.7815	(4,2)	2.9647
(4,0)	2.7823	(2,3)	2.9650
(4,1)	2.8266	(3,1)	2.9692
(4,2)	2.8354	(2,4)	2.9750
(4,3)	2.8524	(0,1)	2.9840
(3,2)	2.8748	(0,2)	2.9882
(1,3)	2.8782	(0,3)	2.9932
(3,1)	2.8783	(2,0)	2.9938
(3,0)	2.8873	(3,4)	2.9959
(1,4)	2.8875	(0,4)	3.0013
(2,2)	2.8893	(2,1)	3.0032
(3,3)	2.8893	(4,3)	3.0092
(2,0)	2.9160	(1,3)	3.0098
(2,4)	2.9164	(2,2)	3.0115
(2,3)	2.9235	(3,0)	3.0173
(1,1)	2.9308	(1,4)	3.0247
(1,2)	2.9333	(3,2)	3.0361
(4,4)	2.9440	(4,1)	3.0414
(1,0)	2.9526	(1,0)	3.1586
(0,4)	2.9984	(0,0)	3.4124
(0,3)	3.0969	(1,1)	3.4602
(3,4)	3.2547	(1,2)	3.4776
(0,2)	3.3189	(4,0)	3.5202
(0,1)	3.5963	(3,3)	3.5464
(0,0)	4.3600	(4,4)	3.5930

In Table 3, we obtain the models named LNV-ARMA using the *LNV-WAFC* dependent variable provided the trend stationarity by the LNV methodology, and the ARIMA models using the *DD-WAFC* dependent variable provided the difference stationarity by the classical differencing method. We use the Generalized Least Squares (GLS) method to estimate the LNV-ARMA models and the Conditional Least Squares-CLS method to estimate the ARIMA models. In selecting the estimation method, the results' significance is decisive. In the table, both groups of models are listed in themselves from smallest to largest according to their AIC values. For each group among these models, the converged and the smallest five models in terms of the AIC values are selected for comparative analysis and shown in Table 4 and Table 5.

Table: 4
LNV-ARMA Models

	Model I	Model II	Model III	Model IV	Model V
	(2,1)	(4,0)	(1,3)	(3,0)	(1,4)
Convergence	18 Iteration	3 Iteration	43 Iteration	4 Iteration	43 Iteration
C (*)	0.0317 (0.8038)	0.1763 (0.6866)	0.6156 (0.5578)	0.3528 (0.6200)	0.5761 (0.5664)
AR(1) (*)	1.9316 (0.0000)	1.0488 (0.0000)	0.8572 (0.0000)	1.1116 (0.0000)	0.8350 (0.0000)
AR(2) (*)	-0.9985 (0.0000)	0.0015 (0.9908)		-0.0091 (0.9484)	
AR(3) (*)		0.1362 (0.3029)		-0.2330 (0.0213)	
AR(4) (*)		-0.3884 (0.0001)			
MA(1) (*)	-0.9110 (0.0000)		0.2208 (0.0532)		0.2397 (0.0736)
MA(2) (*)			0.1791 (0.1070)		0.1784 (0.1502)
MA(3) (*)			0.2581 (0.0149)		0.3000 (0.0104)
MA(4) (*)					0.1054 (0.3680)
R^2	0.8207	0.8120	0.7916	0.7858	0.7932
$\bar{R}^2$	0.8160	0.8055	0.7844	0.7803	0.7841
F-Statistics (*)	176.9699 (0.0000)	124.2109 (0.0000)	109.2214 (0.0000)	141.8622 (0.0000)	87.4485 (0.0000)
AIC	2.7815	2.7823	2.8782	2.8873	2.8875
SIC	2.8745	2.8984	2.9943	2.9802	3.0268
SSR	96.9663	101.6398	112.6822	115.8234	111.8326
LR	-162.8925	-161.9372	-167.6900	-169.2370	-167.2478
Q-Statistics [Lag]	Insignificant [36]	Insignificant [36]	Insignificant [36]	Partially Insignificant [36]	Insignificant [36]
LM Test [Lag] ($P-\chi^2$)	[1] (0.1362)	[1] (0.2439)	[1] (0.3036)	[1] (0.0001)	[1] (0.1446)
White Test ($P-\chi^2$)	0.0708	0.5181	0.0034	0.0643	0.0620

Note: (*) denotes p-values.

When we examine Table 4, we see that all models' AR(1) parameters are significant at 1%. However, we see that the AR(2) parameter is significant at 1% for only Model I, the AR(3) parameter is significant at 5% for only Model IV, and the AR(4) parameter is significant at 1% for Model II. When it comes to the MA components of the models; while the MA(1) parameter is significant at 1% for Model I, the MA(3) parameters are significant at 5% for Model III and Model V. However, the MA(2) parameters for Model III and Model V, the MA(4) parameter for Model V, and the intercept parameters of all models are insignificant. Considering the coefficients of determination and adjusted determination (0.8207 and 0.8160, respectively), we find that Model I is the most explanatory. We see that the F-statistics values are significant for all models. While Model I is the smallest in terms of AIC, SIC, and SSR values, Model II is the largest in terms of LR value. There are no autocorrelation problems except Model IV and heteroscedasticity problems except Model III. Finally, we find that the Q-statistics are insignificant for all models except Model IV and partially insignificant for Model IV. Given all these results, we choose the LNV-ARMA(2,1) model [Model I] as the best model in this group.

Table: 5
ARIMA Models

	Model I	Model II	Model III	Model IV	Model V
	(4,2)	(2,3)	(3,1)	(2,4)	(0,1)
Convergence	46 Iteration	51 Iteration	31 Iteration	46 Iteration	13 Iteration
C (*)	0.0191 (0.6707)	0.0156 (0.6439)	0.0041 (0.6571)	0.0170 (0.6450)	0.0132 (0.6718)
AR(1) (*)	-0.0763 (0.3954)	-1.2327 (0.0000)	0.1737 (0.0655)	-1.2285 (0.0000)	
AR(2) (*)	-0.8727 (0.0000)	-0.9995 (0.0000)	0.1574 (0.0988)	-0.9973 (0.0000)	
AR(3) (*)	-0.4243 (0.0000)		0.2800 (0.0040)		
AR(4) (*)	-0.4053 (0.0000)				
MA(1) (*)	-0.6908 (0.0000)	0.5898 (0.0000)	-0.9816 (0.0000)	0.5296 (0.0000)	-0.6902 (0.0000)
MA(2) (*)	0.9750 (0.0000)	0.1652 (0.0815)		0.1796 (0.0606)	
MA(3) (*)		-0.6393 (0.0000)		-0.5811 (0.0000)	
MA(4) (*)				0.0940 (0.3330)	
R^2	0.4445	0.4236	0.4166	0.4278	0.3594
$\bar{R}^2$	0.4134	0.3974	0.3954	0.3963	0.3539
F-Statistics (*)	14.2722 (0.0000)	16.1671 (0.0000)	19.6375 (0.0000)	13.5815 (0.0000)	65.0743 (0.0000)
AIC	2.9647	2.9650	2.9692	2.9750	2.9840
SIC	3.1328	3.1075	3.0856	3.1411	3.0310
SSR	114.4642	118.7823	120.2221	117.9168	132.0143
LR	-161.9906	-165.9716	-165.7314	-165.5474	-174.0561
Q-Statistics [Lag]	Insignificant [36]	Insignificant [36]	Insignificant [36]	Insignificant [36]	Insignificant [36]
LM Test [Lag] ($P-\chi^2$)	[1] (0.9514)	[1] (0.4000)	[1] (0.5840)	[1] (0.6904)	[1] (0.3129)
White Test ($P-\chi^2$)	0.0769	0.8077	0.2016	0.6307	0.7961

Note: (*) denotes p-values.

When we examine Table 5, we see that the AR(1) parameters are significant at 1% for only Models II and IV. However, the AR(2) parameters are significant at 1% for only Models I, II, and IV. Also, the AR(3) parameters for Models I and III and the AR(4) parameter for Model I are significant at a 1% significance level. Regarding the MA components of the models, we see that the MA(1) parameters are significant for all models at a 1% significance level. However, we see that the MA(2) parameter for only Model I and the MA(3) parameters for Models II and IV are significant at a 1% significance level. But, we find that the MA(4) parameter for Model IV and the intercept parameters of all models are insignificant. Considering the coefficients of determination and adjusted determination (0.4445 and 0.4134, respectively), we find that Model I is the most explanatory. We see that the F-statistics values are significant for all models. While Model I is the smallest in terms of AIC and SSR values and the largest in terms of LR value, Model V is the smallest in terms of SIC value. There are no autocorrelation and heteroscedasticity problems in any of the models. Finally, we find that the Q-statistics are insignificant for all models. Given all these results, we choose the ARIMA(4,2) model [Model I] as the best model in this group.

When we compare the LNV-ARMA(2,1) and the ARIMA(4,2) models in themselves, we see that the best model is LNV-ARMA(2,1). First of all, this model is more dependent on the parsimony principle with less number of parameters and significance (3 significant parameters versus 5) compared to the ARIMA(4,2) model, and is also approximately twice as explanatory ($R^2_{LNV-ARMA(2,1)} = 0.8207$ and $R^2_{ARIMA(4,2)} = 0.4445$). Again, this model is smaller in terms of AIC (2.7815 versus 2.9647), SIC (2.8745 versus 3.1328), and SSR (96.9663 versus 114.4642) values.

5. Concluding Remarks

In this study, we model the monthly time series of the Central Bank of the Republic of Turkey's Weighted Average Funding Cost (CBRT WAFC) for the period between 2011:01-2020:12. In this framework, we establish and compare the linear and the nonlinear based various autoregressive (integrated) moving average [AR(I)MA] models in two separate groups and investigate the most suitable model for the series.

Firstly, we make the stationarity analysis of the series using the linear ADF test, which is widely employed in the unit root tests, and make the series difference stationary by taking the second difference of the series. Then, using this series, we establish various ARIMA models and choose the ARIMA(4,2) as the best model in this group. Secondly, we make the stationarity analysis of the related series by employing the nonlinear unit root test developed by Leybourne et al. (1998) [LNV], which is one of the unit root tests with a break in the mean and/or trend. Using this methodology, we detect and remove the nonlinear deterministic trend from the series and make the series trend stationary. Later, we build various ARMA models using this series and name these models LNV-ARMA models. We choose the LNV-ARMA(2,1) as the best model in this group. Finally, we compare the best models of these two groups and reveal that the CBRT WAFC time series can be modelled best with the LNV-ARMA(2,1) model for the relevant period. This model shows that the current CBRT WAFC is affected by the CBRT WAFC of the previous two periods and the random shocks that occurred in the last period. This case indicates that the market participants, especially banks who follow the value of the CBRT WAFC, should take into account the values of the CBRT WAFC for the last two periods and the previous period shocks that may have an impact on this rate while predicting the current value of the relevant time series.

As stated previously, the CBRT WAFC may be crucial in pricing their products, especially for the banks. In this study, the relevant interest rate is modelled by the LNV methodology, which reveals the CBRT's asymmetric behaviour. In this way, it is indicated that the banks and the other market participants should be careful about possible similar behaviour in the future.

In summary, we can make three main policy implications regarding the CBRT WAFC for the related period. These are the policy maker's asymmetric behaviour, the role of interest rates in previous periods in determining the current period interest rate and being effective of the recent unexpected developments (news) on the current period interest rate.

Modelling of the CBRT WAFC using different linear and nonlinear methodologies apart from the LNV methodology is the subject of further studies that might be conducted after this study.

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