INFLATION FORECAST IN TURKEY: ARIMA PROCEDURE

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ABSTRACT

For hundreds of years, inflation has been the core topic in managing the economy, budgets and any kind of business and funding related strategies. Inflation uncertainities can have a deep impact in individuals, businesses, real and financial sectors. In that regard, correct forecasting of future prices is very important to take proper steps in these activities mentioned in this paragraph.

This paper focuses on the ARIMA applications in forecasting the difference between the today's price and t+1, t+2….t+n's period price in Turkey. To determine which model is useful to properly evaluate the future movements, in this paper the method and conclusion is presented, as well as the other key insights. Thus, at the end of the research, one can determine what would be the proper model to use in inflation forecasting in Turkey.

INTRODUCTION

Central bank policies and its mandate in Turkey is designed as to provide price stability and financial stability. One of the mechanisms for these policies is to provide actions to combat with high inflations. Price stability is very important factor to maintain the economic stability together with unemployment figures.

Inflation is maybe the most closely watched data by the economic actors, so the decisions that are taken under various inflation assumptions are very critical for the overall economy. Inflation figures put enormous pressure on monetary policy authorities, so these authorities tend to make forecasts and assumptions to provide a ground for better monetary policies. Recently, Turkish Central Bank has been bombarded with the critisms that the real interest rates are negative. In response to these critisims, the authorities claimed that based on their calculations inflation is expected to be lesser than their policy rate, which one more emphasizes the importance of forecasting the inflation. In the literature, various methods are developed to make good forecasts and these tools are important in inflation forecasts.

Inflation is not a variable that only the central bank authorities use, the business decisions are very much affected by inflation estimations. Investments, valuations, FX market, many sectors that are sensitive to interest rates and in general overall expectations in the economy are affected by the future inflation figures. In that regard, the future inflation expectation is taken in the account, rather than the lagging data of the previous inflation figures. For example, valuations in M&A deals are affected by the inflation estimations and even have big impact in discounting the future cash flows. Another example, 10 percent return on the investment may look good, but when adjusted for inflation in the country that has unpredictably volatile inflation structure, if the inflation for the period happened to be larger than 10 percent, one cannot claim that this is a good investment. So, finding a reliable model for inflation forecasting is very important as it affects almost everything in the economic machine.

The goal of this research paper is to properly use ARIMA models to reach our goal of predicting inflation figures. The monthly data of 2005-2019 period is used to determine the best model for forecasting. The inflation used here is provided by Tüketici Fiyat Endeksi (TÜFE) and is defined as the overall inflation in the whole economy (not the inflation for some specific type of goods or services).

METHODOLOGY

What is fascinating and most demanded from econometric models is the forecasting ability of these models. Time series forecasting can be vital for economic policies. The past data is used to derive models and make appropriate future forecasts in ARIMA models (Akdi, 2003). In short, past values of dependent variable and its different lagging values can provide a ground to derive their relationship with each other. In that regard, time series models can be built by the help of three tools. These are trend, seasonality and stochastic effects. The following equiation shows how the equation is constructed.

$$Y_t = T_t + S_t + u_t$$

Y is dependent variable, T is trend, S is seasonality and u is stochastic variable in the equation (Ramanathan, 2002).

The steps in determining the most appropriate model for the forecasting process can be summarized in the following paragraphs.

First, a proper and correct data should be obtained, preferably from official authorities or sources that the validity of data could be approved through. Once the data is available, the researcher should determine what type of data should he or she use, will the data be daily, monthly or even yearly? Then the researcher should take a look at the visual representation of the data, graphs, to have some idea and build the first thoughts on how to conduct the research and what models can be used to achieve better results.

After the initial visual representation, the researcher should evaluate the stationarity of the data, as it is a rule of thumb to make forecast through ARIMA models. To evaluate whether the data is stationarity, the time series is tested by tests such as Augmented Dickey-Fuller Test. If the time series is not stationary, the difference between the first lagging values and the current values is taken and a new time series is constructed. The stationarity is tested again. If there is one more need of differencing, it is made by taking the difference of the newly generated time series. It should be noted that after each differencing, a certain amount of information is lost and this could make the forecasts less accurate.

After having a stationary time series, either by taking the difference of the original series or artifically creating one, the next thing is to examine the correlogram of this series. In this paper, Box-Jenkins Methodology, which involves examining plots of the samples, is used. The model identification is easy, if it has a pure AR or MA process. However, in mixed ARIMA (or ARMA) models, interpreting ACFs and PACFs can be challanging, and the procedure is highly subjective. Random noise in time series, especially in financial time series, makes model identification process more problematic (Meyler, Kenny, & Quinn, 1998)

In the pure AR process, the ACF plot decays gradually as lags increase and the PACF plot of a pure AR process would die out after p lags (ARIMA(p,d,q)). For example, PACF of pure AR(2) process should die out after 2 lags, whereas pure AR(8) process would die out after 8 lags. In the pure MA process, the process is the reversed one. Thus, ACF plot of a pure MA(q) process should die out after q lags and the PACF plot of it exhibits geometrically declining pattern (similar to what ACF plot did in pure AR process). As the difference between the lags in PACF plot of pure MA process will be impossible to identify, the spikes in ACF plot will disappear after 3 lags when the process is MA(3) or 5 lags when the process is MA(5) (Meyler, Kenny, & Quinn, 1998).

In the mixed ARIMA process, the model identification is complicated. The patterns of sample autocorrelations and partial autocorrelations are hard to interpret.

After model identification, some diagnostic checking should be done by the researcher. Fitted values and residuals should be evaluated and the spots where the model performed well and bad should be identified. When there are large inconsistencies in the model and the model mostly performed poorly, the previous step should again be performed and a better model should be selected.

The last part of ARIMA procedure is forecasting. One key point in this step is to have a splitted data if the researcher is testing the model using data that does not contain the current dates. When the data is splitted into two parts, one part for model validation and one part for forecasting, the researcher can see from the past data if the model would perform well if it was performed on those dates. The ARIMA model uses the following equation to make forecasts after the model is properly designed. It should be noted that “I” represents the order of differencing.

ARMA(p, q) **model**

- $y_t = a_0 + a_1 y_{t-1} + \ldots + a_p y_{t-p} + e_t + b_1 e_{t-1} + \ldots + b_q e_{t-q}$

where $\boldsymbol{e_t}$ **series are serially uncorrelated "<u>shocks</u>"**

AR(p*)*: <u>Auto-Regressive</u> of order (p)

- $y_t = a_0 + a_1 y_{t-1} + \ldots + a_p y_{t-p} + e_t$

MA(q): Moving-Average of order (q)

- $x_t = \sum_{i=0}^{q} \beta_i \varepsilon_{t-i}$

Overall, the ARIMA forecasting procedure is listed as follows:

1) Data Collection and Examination
2) Determine Stationarity of Time Series
3) Model Identification and Estimation
4) Diagnostic Checking
5) Forecasting and Forecast Evaluation

LITERATURE REVIEW

ARIMA process in forecasting inflation is generally done by the aim of comparing the models by their predictive ability. The other and most important function of forecasting through ARIMA in inflation time series is to correctly forecast the future inflation figures. As it is well-known, above-expected or below-expected results of inflation can lead to significant changes in the economy and the decisions of economic actors.

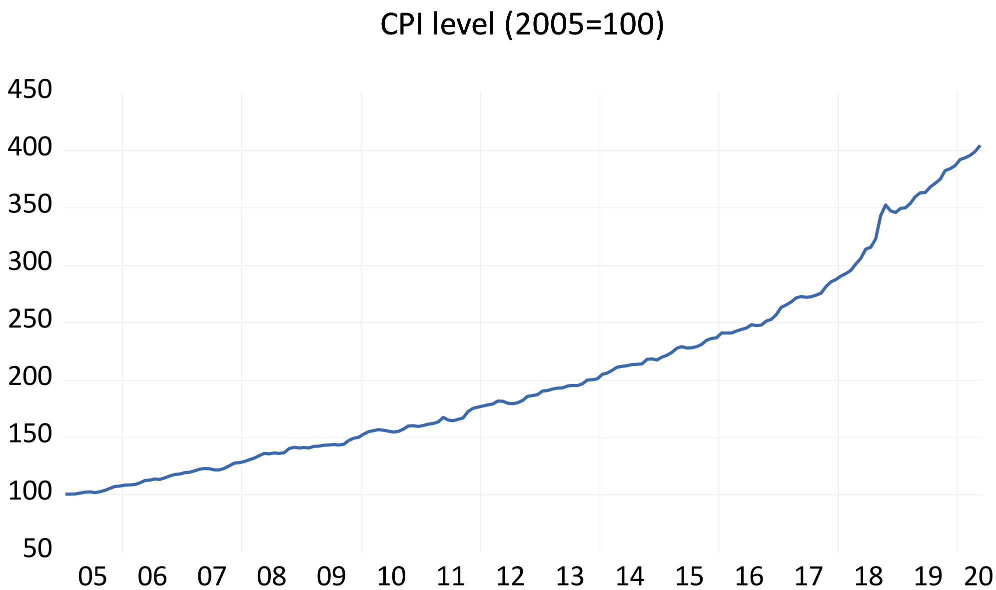
Inflation uncertainity costs much to the economy and real economy also affected negatively by this, as well as the financial industry (Özer & Türkyılmaz, 2005). Besides that, inflation expectations shape the consumption, investment and saving decisions of economic actors. So, policy makers make an extra effort to collect the data that could have significant impact in the future inflation (Lyziak, 2003).

There are plenty of research done on inflation forecasting through ARIMA models in the literature. (Bokhari & Feridun, 2006), Meyler, Kenny and Quinn (1998), (Owusu, 2010), (Pervaiz, 2005), (Krkoska & Teksoz, 2006), (Pufnik & Kunovac, 2006), (Salam, Salam, & Feridun, 2006), (Haider & Hanif, 2009), (Uğurlu & Saraçoğlu, 2010), (Meçik & Karabacak, 2011) concluded that ARIMA models have a good predictive power in forecasting inflation.

Among the popular methods in inflation forecasting is Phillips curve method. The adverse relationship between the unemployment and the inflation figures is used by this special formula to better evaluate the future charasteristics of the inputs and outputs of the formula (Stock & Watson, 1999).

RESULTS AND DISCUSSION

First, monthly inflation data was obtained from Turkish Central Bank’s website. The data contained dates between January 2005-May 2020, a total of 185 observations, which is more than the least recommended amount of 50 observations (Meyler, A, G. Kenny and T. Quinn, 1998). This data shows monthly inflation and this is then turned into a cumulative representation of overall CPI level in the last 15 years (2005=100). So, by looking at the visual representation we can better obtain information regarding how the overall prices evolved. There is no structural break in this time series and the data satisfies necessary conditions to conduct this research.



The trend is obvious in this graph, as in the almost all CPI level graphs, and there are jumps from time to time. For example, high inflation in August 2018 can easily be observed through looking at this data (the time when Turkish lira devalued at an unprecedented rate in just couple of days). By looking at this visual representation, it is difficult to conclude that the graph is stationary. Thus, Augmented Dickey-Fuller Test should be conducted.

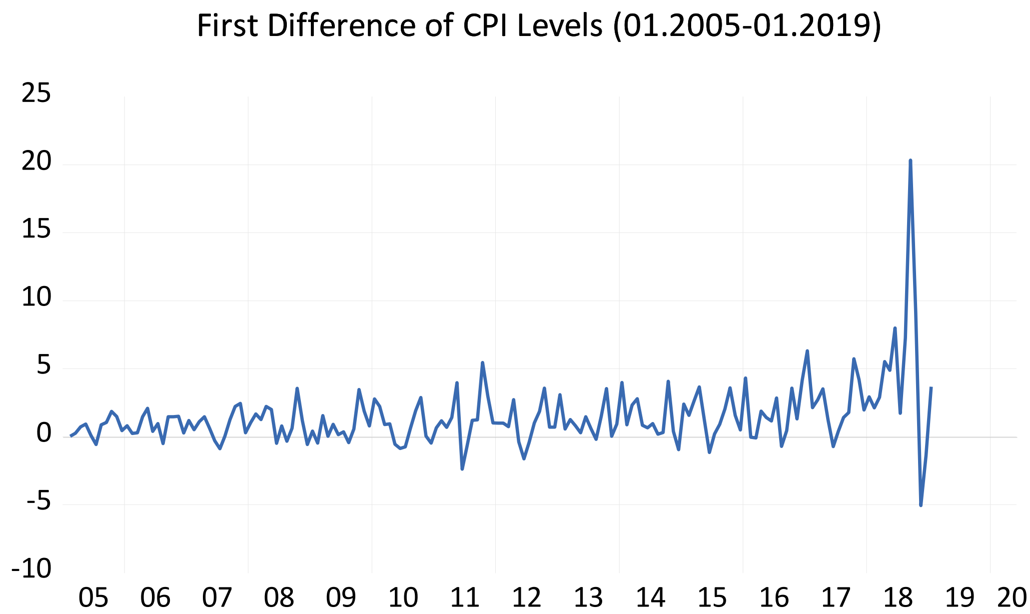
		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.955166	1.0000
Test critical values:	1% level	-4.010143	
	5% level	-3.435125	
	10% level	-3.141565	

The test result dictates that the cumulative representation of monthly inflation figures (CPI level) is not stationary as the p-value is equal to one. An order of differencing is needed to obtain an artificially created stationary data.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.978	0.978	179.96	0.000
		2	0.957	-0.007	353.03	0.000
		3	0.936	-0.007	519.39	0.000
		4	0.914	-0.014	679.09	0.000
		5	0.892	-0.016	832.15	0.000
		6	0.871	-0.002	978.83	0.000
		7	0.850	-0.016	1119.2	0.000
		8	0.828	-0.017	1253.2	0.000
		9	0.807	0.009	1381.2	0.000
		10	0.787	-0.005	1503.6	0.000
		11	0.766	-0.007	1620.4	0.000
		12	0.746	-0.004	1731.7	0.000
		13	0.726	-0.024	1837.7	0.000
		14	0.705	-0.010	1938.3	0.000
		15	0.685	0.002	2033.9	0.000
		16	0.666	-0.006	2124.6	0.000
		17	0.646	-0.016	2210.5	0.000
		18	0.626	-0.009	2291.7	0.000
		19	0.606	-0.028	2368.2	0.000
		20	0.584	-0.044	2439.8	0.000
		21	0.564	0.012	2506.8	0.000
		22	0.546	0.057	2570.0	0.000
		23	0.529	0.014	2629.9	0.000
		24	0.513	-0.013	2686.3	0.000
		25	0.497	0.010	2739.7	0.000
		26	0.482	0.002	2790.2	0.000
		27	0.467	0.006	2838.0	0.000
		28	0.453	-0.007	2883.2	0.000
		29	0.439	-0.008	2926.0	0.000
		30	0.425	-0.004	2966.2	0.000
		31	0.411	-0.011	3004.1	0.000
		32	0.397	0.001	3039.8	0.000
		33	0.384	0.008	3073.4	0.000
		34	0.371	-0.008	3105.0	0.000
		35	0.359	-0.005	3134.6	0.000
		36	0.346	-0.013	3162.4	0.000

Another way to visualize the data is to look its correlogram plots (ACF and PACF). If the ACF plot decays slowly and remains high for half a dozen or more lags, the time series is not stationary (Chiu & Tavella, 2008). In that regard, correlogram also states that this time series is not stationary. In order to derive proper ARIMA, AR(p) or MA(q) model, the time series should be made stationary by differencing, as stated above.

After the first look, rather than using the whole data for the overall process, the data is splitted into two parts (January 2005-January 2019 and February 2019-May 2020). The first part is to be used for model validation and the second part is to be used to evalute the forecast that our model made.

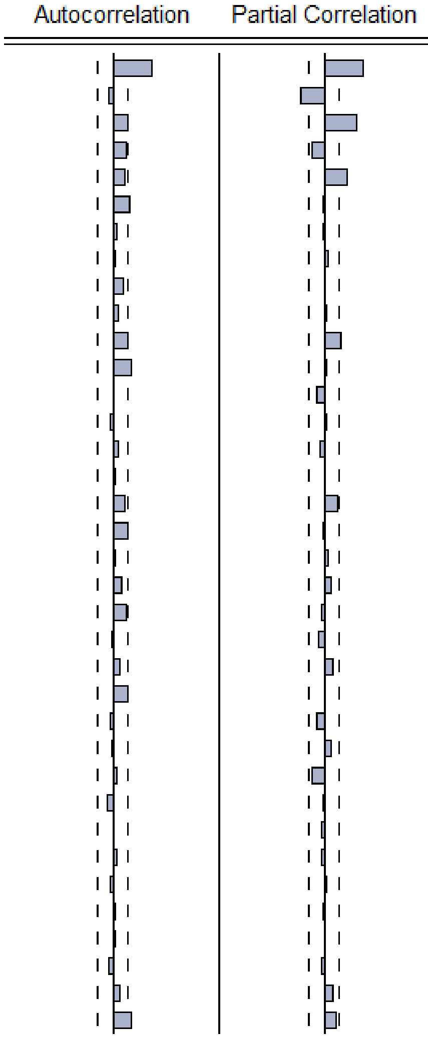


Differenciated data looks more like a stationary data as it seems to have a constant mean over time (it also should have a constant standard deviation that does not statistically significantly change over time). However, this is just an initial guess, Augmented Dickey-Fuller Test is again to be done to reach a conclusion about stationarity.

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.936906	0.0022
Test critical values:	1% level	-3.466994	
	5% level	-2.877544	
	10% level	-2.575381	

*MacKinnon (1996) one-sided p-values.

So, the conclusion is that this time series is stationary as the t-statistics of Augmented Dickey-Fuller test is even above the 1% level. The following correlogram graph also gives us idea about the stationarity of the data.



Lag	AC	PAC	Q-Stat	Prob
1	0.388	0.388	25.714	0.000
2	-0.046	-0.231	26.080	0.000
3	0.143	0.316	29.610	0.000
4	0.132	-0.120	32.646	0.000
5	0.111	0.223	34.812	0.000
6	0.157	-0.015	39.151	0.000
7	0.049	-0.002	39.577	0.000
8	0.030	0.042	39.742	0.000
9	0.091	0.007	41.244	0.000
10	0.060	0.020	41.896	0.000
11	0.142	0.156	45.565	0.000
12	0.188	0.026	52.021	0.000
13	0.007	-0.070	52.030	0.000
14	-0.024	0.019	52.137	0.000
15	0.056	-0.041	52.728	0.000
16	0.023	0.000	52.827	0.000
17	0.110	0.127	55.119	0.000
18	0.145	-0.003	59.138	0.000
19	0.030	0.038	59.307	0.000
20	0.087	0.080	60.756	0.000
21	0.127	-0.017	63.868	0.000
22	-0.006	-0.062	63.876	0.000
23	0.067	0.089	64.748	0.000
24	0.148	0.005	69.094	0.000
25	-0.027	-0.073	69.236	0.000
26	-0.003	0.077	69.238	0.000
27	0.044	-0.112	69.635	0.000
28	-0.050	-0.007	70.137	0.000
29	0.016	-0.020	70.187	0.000
30	0.040	-0.032	70.520	0.000
31	-0.026	0.030	70.656	0.000
32	0.022	-0.013	70.761	0.000
33	0.026	0.011	70.904	0.000
34	-0.040	-0.023	71.245	0.000
35	0.073	0.088	72.382	0.000
36	0.183	0.118	79.634	0.000

The ACF plot is decaying rapidly from its initial value at zero lag as opposed to the previous correlogram. This suggests that the data is stationary. Also, the slowly declining partial autocorrelation states that this could be an MA(1) process. The autocorrelations at lags 12, 24 and 36 exhibit distinctive behaviour and are indicative of seasonality in the data (Meyler et al., 1998). As the seasonality is being suspected in the data, one way is to support the hypothesis is to regress the original data over its seasonal differences from 1 to 12. It can easily be conducted in Eviews using the formula of *d(x, n, s)* (n^{th} order difference with a seasonal difference at *s*). In this sense, d(cpi_level, 0, 1).

Dependent Variable: CPI_LEVEL (non-differenced original cumulative data)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	110.8135	5.473173	20.24667	0.0000
D(CPI_LEVEL,0,1)	1.255183	2.715706	0.462194	0.6446
D(CPI_LEVEL,0,2)	-1.423649	3.150390	-0.451896	0.6520
D(CPI_LEVEL,0,3)	1.704421	3.435032	0.496188	0.6205
D(CPI_LEVEL,0,4)	-0.763589	3.601596	-0.212014	0.8324
D(CPI_LEVEL,0,5)	-0.882802	3.804576	-0.232037	0.8168
D(CPI_LEVEL,0,6)	-1.567917	3.851679	-0.407074	0.6846
D(CPI_LEVEL,0,7)	0.175589	3.955537	0.044391	0.9647
D(CPI_LEVEL,0,8)	1.026703	3.993328	0.257105	0.7975
D(CPI_LEVEL,0,9)	-1.083709	3.831189	-0.282865	0.7777
D(CPI_LEVEL,0,10)	0.251051	3.737484	0.067171	0.9465
D(CPI_LEVEL,0,11)	-0.151849	3.726698	-0.040746	0.9676
D(CPI_LEVEL,0,12)	6.032745	2.284808	2.640372	0.0092

R-squared	0.709255	Mean dependent var	193.1733
Adjusted R-squared	0.685027	S.D. dependent var	61.28906
S.E. of regression	34.39695	Akaike info criterion	9.992985
Sum squared resid	170373.6	Schwarz criterion	10.24605
Log likelihood	-771.4494	Hannan-Quinn criter.	10.09576
F-statistic	29.27332	Durbin-Watson stat	0.089916
Prob(F-statistic)	0.000000		

In this OLS regression, it is obvious that the seasonal difference at lag 12 has a significant effect on determining the dependent variable as the p-value of the test is 0.0092, more than enough to reject that the coefficient at lag 12 is zero. Thus, seasonal differencing should be used together with the firstly differenciated original data to have a stationary data and to take into account the seasonality that we concluded above. Initial conclusion is that this is an MA(1) process.

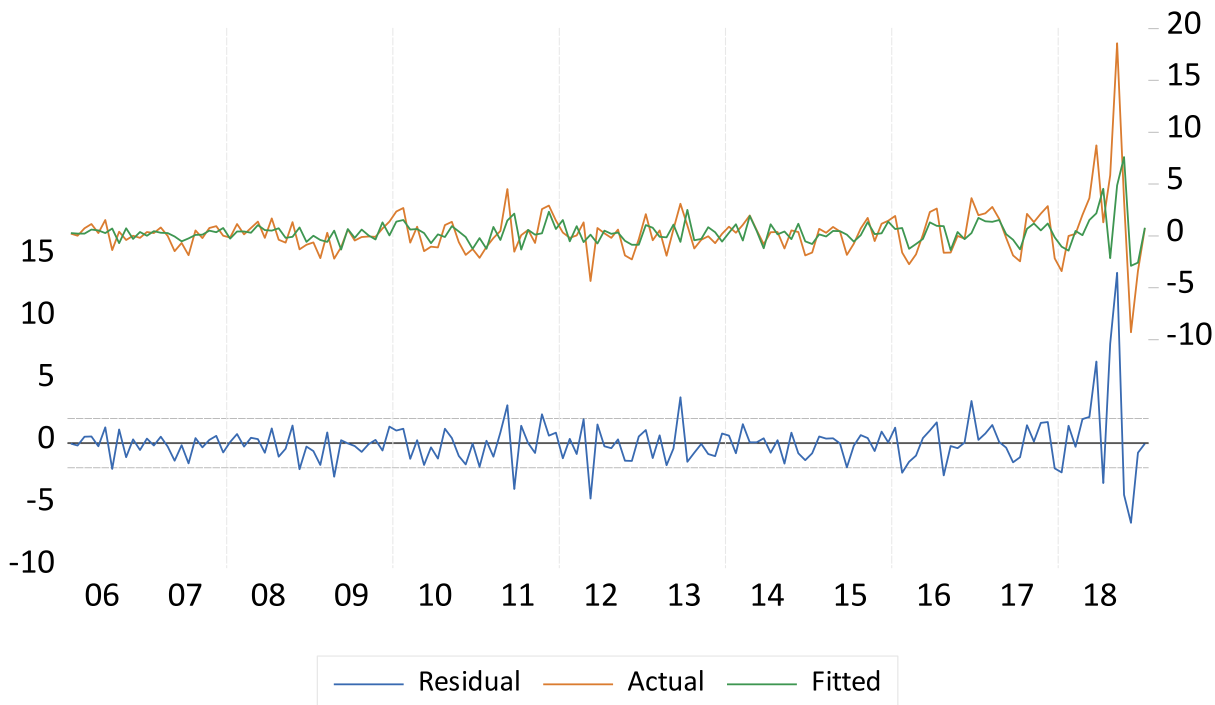
As a next step, d(cpi_level, 1, 12) (first order of difference with a seasonal difference at lag 12) should be regressed over a constant and MA(1) term, using a software such as Eviews.

Dependent Variable: D(CPI_LEVEL,1,12)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.328719	0.307965	1.067393	0.2875
MA(1)	0.556760	0.036700	15.17045	0.0000
SIGMASQ	4.567803	0.304905	14.98105	0.0000

R-squared	0.184734	Mean dependent var	0.327892
Adjusted R-squared	0.174077	S.D. dependent var	2.374655
S.E. of regression	2.158094	Akaike info criterion	4.397749
Sum squared resid	712.5773	Schwarz criterion	4.456401
Log likelihood	-340.0245	Hannan-Quinn criter.	4.421571
F-statistic	17.33440	Durbin-Watson stat	2.149576
Prob(F-statistic)	0.000000		

The MA(1) term is statistically significant and the model looks appropriate at this step. Further examionation involves looking at the residuals and fitted values.

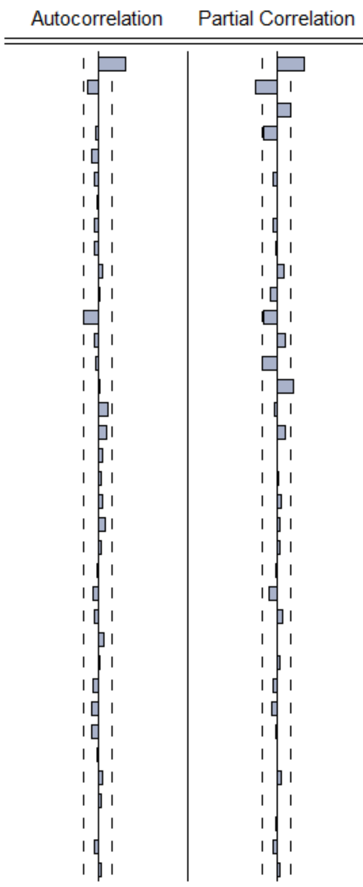


The model did a satisfying job until mid-2018. MA(1) model cannot adequately predict the unprecedented volatility starting from August 2018. As the graph clearly shows, the difference between actual and fitted values grow and there are big jumps in residuals around that time.

Before mid-2018, there are few cases when the residuals reached the boundaries represented with two lines. It would give a more comprehensive idea to look at the correlogram of the residuals.

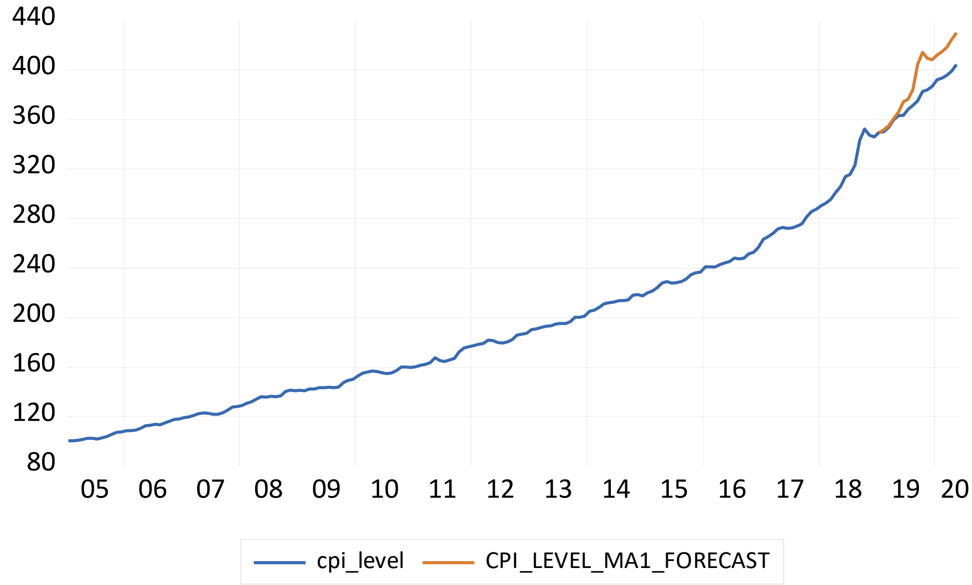
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.075	-0.075	0.8913	
		2	-0.106	-0.112	2.6919	0.101
		3	0.067	0.050	3.4097	0.182
		4	-0.025	-0.028	3.5071	0.320
		5	-0.054	-0.046	3.9837	0.408
		6	-0.011	-0.029	4.0049	0.549
		7	-0.001	-0.012	4.0050	0.676
		8	-0.017	-0.018	4.0550	0.773
		9	-0.044	-0.050	4.3742	0.822
		10	0.030	0.017	4.5309	0.873
		11	0.110	0.106	6.5997	0.763
		12	-0.248	-0.232	17.109	0.105
		13	0.105	0.096	19.013	0.088
		14	-0.086	-0.154	20.282	0.088
		15	0.026	0.081	20.396	0.118
		16	0.091	0.054	21.864	0.111
		17	0.031	0.052	22.031	0.142
		18	0.042	0.060	22.350	0.172
		19	0.009	0.007	22.365	0.216
		20	0.022	0.042	22.453	0.262
		21	0.065	0.064	23.223	0.278
		22	0.010	0.032	23.242	0.331
		23	-0.007	0.073	23.250	0.388
		24	-0.011	-0.090	23.273	0.445
		25	-0.084	0.011	24.599	0.428
		26	0.114	0.033	27.052	0.353
		27	-0.018	0.026	27.111	0.404
		28	-0.022	0.018	27.203	0.453
		29	-0.043	-0.063	27.567	0.488
		30	-0.052	-0.026	28.103	0.512
		31	-0.000	-0.027	28.103	0.565
		32	0.049	0.050	28.580	0.591
		33	0.004	0.020	28.583	0.640
		34	0.031	0.026	28.777	0.678
		35	-0.074	-0.064	29.883	0.670
		36	0.049	0.021	30.382	0.691

When the model does good job, we would normally expect that error-term has a random walk, meaning that we should not see spikes neither in ACF nor PACF plots. However, at lag length 12, there are spikes in both plots suggesting to revise our model and come up with a better one.



	AC	PAC	Q-Stat	Prob
1	0.326	0.326	16.872	0.000
2	-0.116	-0.249	19.034	0.000
3	0.014	0.170	19.065	0.000
4	-0.021	-0.147	19.137	0.001
5	-0.078	0.016	20.122	0.001
6	-0.038	-0.044	20.362	0.002
7	-0.014	0.001	20.396	0.005
8	-0.041	-0.048	20.670	0.008
9	-0.041	-0.014	20.956	0.013
10	0.062	0.083	21.614	0.017
11	0.019	-0.068	21.677	0.027
12	-0.167	-0.146	26.441	0.009
13	-0.038	0.092	26.694	0.014
14	-0.032	-0.160	26.867	0.020
15	0.029	0.196	27.018	0.029
16	0.123	-0.027	29.666	0.020
17	0.093	0.099	31.204	0.019
18	0.063	0.009	31.911	0.023
19	0.040	0.025	32.194	0.030
20	0.058	0.064	32.796	0.036
21	0.084	0.047	34.083	0.036
22	0.037	0.046	34.334	0.045
23	-0.008	-0.002	34.346	0.060
24	-0.053	-0.084	34.877	0.070
25	-0.043	0.077	35.232	0.084
26	0.075	0.004	36.287	0.087
27	0.023	0.035	36.388	0.107
28	-0.051	-0.037	36.887	0.121
29	-0.080	-0.057	38.116	0.120
30	-0.075	-0.009	39.221	0.121
31	-0.002	0.006	39.222	0.148
32	0.054	0.058	39.793	0.162
33	0.040	0.003	40.121	0.184
34	0.002	-0.012	40.122	0.217
35	-0.042	-0.045	40.475	0.241
36	0.046	0.046	40.911	0.264

Seasonal CPI level's correlogram suggest that it's an MA process, because PACF plot is slowly declining whereas spikes in ACF plot disappeared immediately. However, spike at 12th lag could give us an idea to add a second term in our model which is MA(12). Before adding this term and comparing it to this model, let's examine how the forecast would be with this model.



Comparing to the actual CPI level, the forecast values (February 2019-May 2020) cannot really capture the change in the real values. Thus, this result further supported the idea that the model should be modified.

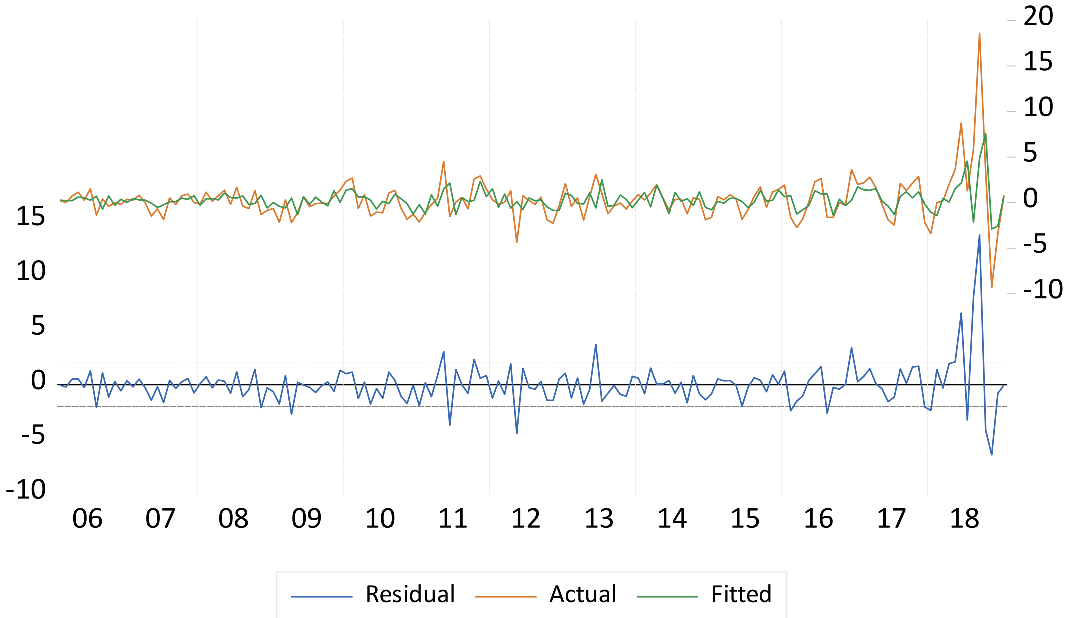
Dependent Variable: D(CPI_LEVEL,1,12)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/27/20 Time: 19:01
Sample: 2006M02 2019M01
Included observations: 156
Failure to improve objective (non-zero gradients) after 23 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.281088	0.229492	1.224823	0.2225
MA(1)	0.585309	0.038802	15.08467	0.0000
MA(12)	-0.414691	0.060736	-6.827796	0.0000
SIGMASQ	3.829760	0.262783	14.57385	0.0000

R-squared	0.316461	Mean dependent var	0.327892
Adjusted R-squared	0.302970	S.D. dependent var	2.374655
S.E. of regression	1.982560	Akaike info criterion	4.269526
Sum squared resid	597.4425	Schwarz criterion	4.347727
Log likelihood	-329.0230	Hannan-Quinn criter.	4.301288
F-statistic	23.45734	Durbin-Watson stat	1.997234
Prob(F-statistic)	0.000000		

Inverted MA Roots	.89	.77+.46i	.77-.46i	.42+.80i
	.42-.80i	-.04-.92i	-.04+.92i	-.52+.79i
	-.52-.79i	-.87+.45i	-.87-.45i	-1.00

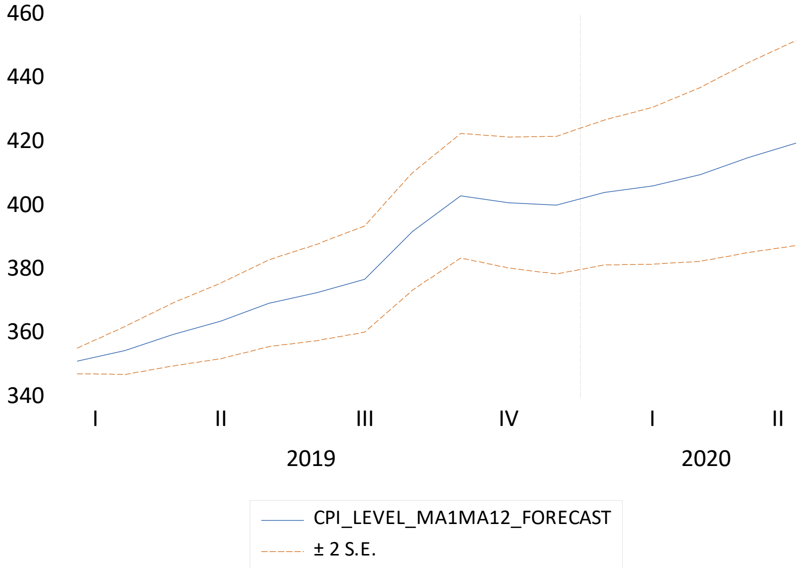
When MA(12) term added to the model, the model is actually improved as MA(12) term is statistically significant and both Akaike info criterion and Schwarz criterion (along with other criterion) are smaller than the previous model, suggesting that this model is better than the only-MA(1) one.



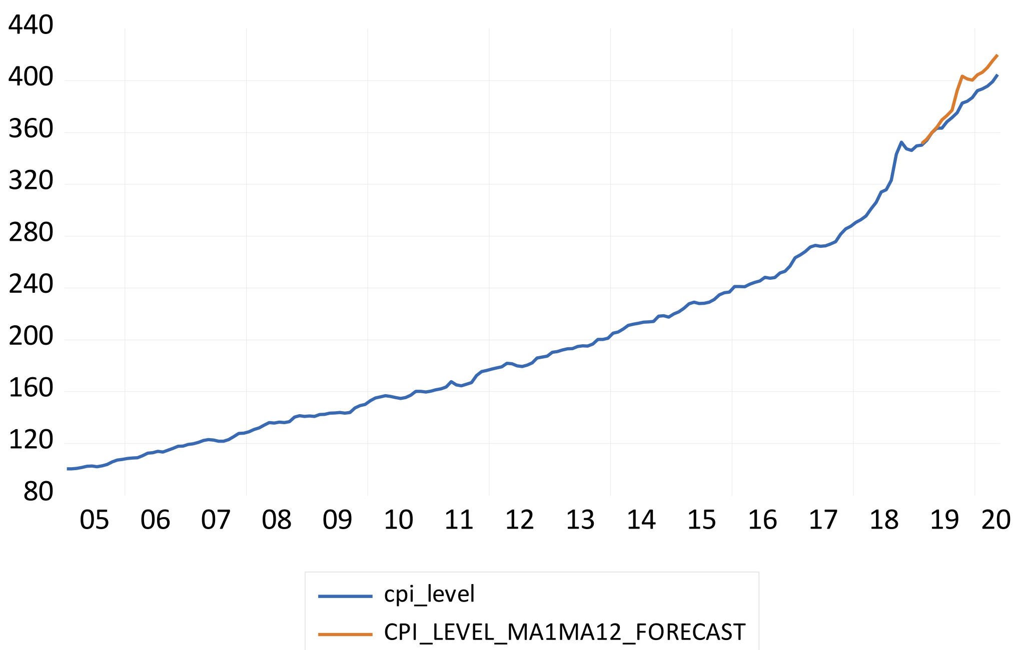
The graph that shows the actual values, fitted values and residuals is not enough to discriminate this model from our previous one, as the spikes and the behaviour of the model looks very similar to each other. MA(1) and MA(12) together also cannot capture the shock in the mid-August. The diagnosis check for the residuals could give a better idea.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0003	
		2	-0.156	-0.156	3.8793	
		3	0.083	0.086	5.0010	0.025
		4	-0.019	-0.047	5.0622	0.080
		5	-0.051	-0.024	5.4805	0.140
		6	0.006	-0.010	5.4874	0.241
		7	-0.002	-0.009	5.4882	0.359
		8	-0.056	-0.053	6.0191	0.421
		9	-0.010	-0.012	6.0345	0.536
		10	0.041	0.025	6.3177	0.612
		11	0.089	0.096	7.6537	0.569
		12	-0.116	-0.116	9.9517	0.445
		13	-0.038	-0.015	10.204	0.512
		14	0.009	-0.042	10.219	0.597
		15	-0.017	0.002	10.268	0.672
		16	0.087	0.088	11.611	0.637
		17	0.042	0.032	11.931	0.684
		18	0.036	0.068	12.160	0.733
		19	0.001	0.002	12.160	0.790
		20	0.048	0.052	12.570	0.816
		21	0.077	0.073	13.641	0.804
		22	-0.005	0.010	13.647	0.848
		23	0.017	0.066	13.701	0.882
		24	-0.090	-0.104	15.219	0.853
		25	-0.028	-0.004	15.371	0.881
		26	0.090	0.066	16.913	0.852
		27	-0.020	-0.033	16.987	0.882
		28	-0.010	0.040	17.008	0.909
		29	-0.059	-0.090	17.673	0.913
		30	-0.050	-0.026	18.169	0.922
		31	0.015	-0.007	18.211	0.940
		32	0.031	0.006	18.407	0.952
		33	0.018	0.047	18.474	0.963
		34	0.026	0.017	18.615	0.971
		35	-0.052	-0.034	19.162	0.974
		36	0.026	0.003	19.299	0.980

In the correlogram there are not any statistically significant spikes that can cause the residuals to behave in a non-random way, in other words, the residuals have a random walk. This is rather important to evaluate the model's effectiveness because when the error term has a random distribution, it has no significant impact on the dependent variable.



Forecast: CPI_LEVEL_MA1MA12_FORECAST	
Actual: CPI_LEVEL	
Forecast sample: 2019M02 2020M05	
Included observations: 16	
Root Mean Squared Error	11.99963
Mean Absolute Error	9.928600
Mean Abs. Percent Error	2.568923
Theil Inequality Coef.	0.015655
Bias Proportion	0.684075
Variance Proportion	0.236641
Covariance Proportion	0.079284
Theil U2 Coefficient	2.951952
Symmetric MAPE	2.522023



Looking at the forecasted values, it is easily realizable that the model does a better better job. The difference between the forecasted values and the actual values is lower than the only-MA(1) model. Below you can find the detailed table regarding these two models.

	CPI_LEVEL	CPI_LEVEL_MA1_FORECAST	CPI_LEVEL_MA1MA12_FORECAST
2019M02	350.2510	351.8247	351.5010
2019M03	353.8586	355.0511	354.7877
2019M04	359.8388	360.9074	359.8079
2019M05	363.2572	366.1143	364.0809
2019M06	363.3662	374.4297	369.6399
2019M07	368.3080	376.4853	372.9885
2019M08	371.4754	384.0754	377.2005
2019M09	375.1531	404.7516	392.1652
2019M10	382.6561	414.2470	403.3495
2019M11	384.1102	409.4999	401.2014
2019M12	386.9526	408.4390	400.4141
2020M01	392.1765	412.1188	404.3847
2020M02	393.5491	414.8975	406.4753
2020M03	395.7923	418.4526	410.0431
2020M04	399.1566	424.6377	415.3444
2020M05	404.5851	430.1733	419.8985

It's also evident in this table that MA(1)-MA(12) model has a better predictive ability than only-MA(1) model. However, in both cases the forecasted values are are not satisfying as the more time the forecast covers, the more difference there is. In May 2020, MA(1)-MA(12) model's forecasted value is 419.9 whereas the actual value is 404.6. Altough almost 4 percent difference in these values can be open to discussion whether the model has no predictive ability at all, the situation is depends more on which country's inflation figures we are estimating. If it was UK or simply a country in EU, we could conclude that the model is not useful, since the yearly inflation in these areas is below 2 percent (4 percent makes huge difference). However, the yearly inflation figures in Turkey varied from 10 to 20 percent in the last three years, so 4 percent difference between forecasted values and actual values in 1.5 years could not considered to be "very unuseful" forecast.

It should also be noted that the external shock to Turkish Lira in August 2018 affected our model and the model tried to capture the spikes in 2018 and took them as an input to forecast the values between February 2019-May 2020.

Overall the model used in inflation forecast for February 2019-May 2020 is the following:

$Yt = 0.28 + 0.59\varepsilon_{t-1} - 0.41\varepsilon_{t-12}$ where $Yt = (1\text{-}L)(1\text{-}L^{12})(CPI\_LEVEL)$

CONCLUSION

This research aimed to select the best and accurate model by using the proper steps outlined in methodology part. The data is collected from Turkish Central Bank's website and is later made stationary through differencing. Through various tools such as ACF and PACF plots, the model identification is done. To evaluate the appropriateness of the model, some diagnostic checking such as looking at the correlogram of the residuals is done. After that the model is modified by adding an additional term. Then the performance is evaluated and two different models were compared.

The statements above can be summarized in the following steps:

1) Data collection and verification
2) Visualisation of the data and emerging of first thoughts, reaching to a conclusion that the data has an upward trend that is getting steeper as the time passes
3) Differencing of the data after Augmented Dickey-Fuller Test stated that the data originally is not stationary
4) Examining the ACF and PACF plots and deciding on MA(1) model together with adding seasonality to the model after realizing spikes at every 12^{th} lag on ACF plot
5) Fitted-actual values and residuals diagnostic checking after building the model and concluding that the model did poor job after mid-2018 when Turkish Lira crisis emerged

6) Further concluding that the residuals do not have a random walk and the addition of MA(12) due to the spike at 12th lag
7) Concluding that MA(1) and MA(12) has better explanatory power together after examining both AIC and Schwarz info criterion, which are smaller than the only-MA(1) model
8) Comparing the forecasting performance of only-MA(1) and MA(1)-MA(12) model, and reaching to a conclusion that the latter one also has better forecasting performance

The model has somehow not bad predictive ability if we compare it to the monthly inflation data. However, when the period gets longer the cumulative effect of the forecast makes the forecasts for further periods less accurate. Also, it is obvious that ARIMA models are vulnerable to external shocks as in the case of Turkish Lira crisis in August 2018. Our model put much emphasis on the spikes in 2018 and forecasted that there would be similar spikes in 2019, but the spikes happened to be rather trivial in 2019. In this example of forecasting inflation in Turkey, ARIMA models have better performance for the near future whereas the forecasted values for far future might significantly diverge from reality.

REFERENCES

Akdi, Y. (2003). *Zaman Serileri Analizi (Birim Kökler ve Kointegrasyon).* Bıçaklar Kitabevi.

Bokhari, S. M., & Feridun, M. (2006). Forecasting Inflation Through Econometric Models: An Empirical Study on Pakistani Data. *Doğuş Üniversitesi Dergisi, 7(1)*, 39-47.

Chiu, S., & Tavella, D. (2008). *Data Mining and Market Intelligence for Optimal Marketing Returns, 1st ed.* Amsterdam: Butterworth-Heinemann/Elsevier.

Haider, A., & Hanif, M. N. (2009). Inflation Forecasting in Pakistan Using Artificial Neural Networks. *Pakistan Economic and Social Review*, 123-138.

Krkoska, L., & Teksoz, U. (2006). Forecasting Inflation for Transition Countries: How Accurate Are The EBRD Forecasts?". *Working Paper No.98, European Bank for Reconstruction and Development*.

Lyziak, T. (2003). Consumer Inflation Expectations in Poland. *Working Paper No.287, European Central Bank*.

Meçik, O., & Karabacak, M. (2011). *ARIMA Modelleri ile Enflasyon Tahminlemesi: Türkiye Uygulaması.*

Meyler, A., Kenny, G., & Quinn, T. (1998). Forecasting Irish Inflation Using. *MPRA Paper No.11359*, 1-46.

Owusu, F. K. (2010). Time Series ARIMA Modelling of Inflation in Ghana: (1990-2009). *Master of Science Thesis Kwame Nkrumah University, Science and Technology Department*.

Özer, M., & Türkyılmaz, S. (2005). Türkiye'de Enflasyon ile Enflasyon Belirsizliği. *İktisat, İşletme ve Finans Dergisi,*, 93-104.

Pervaiz, M. K. (2005). Modeling and Forecasting Pakistan's Inflation by Using Time Series Arima Model. *European Journal of Scientific Research, 9*, 65-99.

Pufnik, A., & Kunovac, D. (2006). Short-Term Forecasting of Inflation in Crotia with Seasonal ARIMA Processes. *Working Paper W-16, Croatian National Bank*.

Ramanathan, R. (2002). *Introductory Econometrics with Applications.* Ohio: SouthWestern Thomson Learning.

Salam, M. A., Salam, S., & Feridun, M. (2006). Forecasting Inflation in Developing Nations: The Case of Pakistan. *International Research Journal of Finance and Economics, 3*, 138-159.

Stock, J. H., & Watson, M. W. (1999). *Forecasting Inflation.* Working Paper 7023, NBER Working Paper Series, Cambridge.

Uğurlu, E., & Saraçoğlu, B. (2010). Türkiye'de Enflasyon Hedeflemesi ve Enflasyonun Öngörüsü. *Dokuz Eylül Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 25(2)*, 57-72.