Chapter 9
Comparative Study of Static and Dynamic ARIMA Models in Forecasting of Seasonally Headline Inflation

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Abstract Consumer Price Index (CPI) is a common indicator of headline inflation. CPI measures the market value of a fixed basket of goods in order to define the inflation of a country's economy. Headline inflation is the measure of the whole inflation in an economy, which consists of all goods, such a price of consumables and energy, which are volatile and prone to inflationary spikes. Headline inflation is usually related to the shift of living cost, which provides useful information to market consumers. The current paper aims at modelling and forecasting the headline inflation in the case of Greece using the Box–Jenkins methodology for the period 2009:1–2020:12. For this purpose, the ARIMA (6,1,6) model was applied. We estimated the ARIMA (6,1,6) model following the maximum-likelihood approach. We maximized the likelihood by iterating the Marquardt and Berndt–Hall-Hall–Hausman algorithms while using numeric derivatives, the optimum step scale and a convergence criterion for the change in the norm of the parameter vector from one iteration to the next. Finally, in order to forecast the headline inflation through the ARIMA(6,1,6) model, a dynamic process and a static process have been applied. The results of the forecasting process suggest that the static process provides a better forecast comparing to the dynamic one.

Keywords Headline inflation · ARIMA model · Box · Jenkins methodology · Forecasting · Greece

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9.1 Introduction

According to Friedman (1968), "*inflation is a steady and sustained increase in the general price level*". The constant increase of inflation follows a steady pace when inflation is derived from economic or other fluctuations.

Similarly, Laidler and Parkin (1975) defined inflation as "*a process of continuously rising prices, or, equivalently, of a continuously falling value of money*". Nevertheless, the definition of core inflation as a component reflects the trend, which characterizes inflation as a measuring trend of headline inflation.

Headline inflation is a measure of the whole inflation in an economy, which consists of all goods, such a price of consumables and energy, which are volatile and prone to inflationary spikes. The headline inflation movements are a combination of the movements of the underlying trend inflation percentage as well as the transitory price movements. On the other hand, "core inflation" or else "underlying inflation" is calculated from the consumer price index excluding the prices of food and energy (oil and energy). The various measures of core inflation (less food and energy) represent the different approaches to stripping the transitory price movements. The degree to which a core measurement successfully reflects the underlying inflation trend is usually assessed by its ability to forecast the headline inflation in the mid-term horizon of 1–2 years (Stardev, 2010).

Headline inflation is the raw inflation figure, which refers to the consumer price index (CPI) and is being published monthly. CPI measures the market value of a fixed basket of goods in order to determine the inflation of each country. CPI uses a year as a basis and calculates the value of the current year according to the value of the basis one. There are a number of indices that can be used for the calculation of CPI. All indices use the information on prices and quantities and collect them in various ways. A price index can accumulate prices and quantities of the basis period, as well as information on prices and quantities of the later period. The values of the price indices can be defined either in terms of real or hypothetical expenses or as weighted averages. The total inflation could present an accurate picture of the inflation trend of an economy, while the sector-specific inflation spikes are unlikely to persist.

If a measure of core inflation includes information, which is useful for the percentage of headline inflation in a future date, it necessarily follows that when there is a difference between headline and core inflation at the current period, then headline inflation, to some extent, reverts back to the core inflation (Gamber et al., 2015).

Core inflation is not adjusted to seasonality or to the frequently unstable elements of food or energy prices, which are removed in the core of the CPI. Headline inflation is usually presented on a yearly basis, which means that a monthly headline inflation of 4% refers to the monthly rate, which if repeated for 12 months will generate 4% inflation for the whole year. Comparisons of headline inflation usually occur monthly, known as top-line inflation. As core inflation includes all aspects in an economy, which experience inflation, it is not adjusted to exclude very unstable figures including those which could shift regardless of the economic conditions. Headline inflation is often related to the shifts of the cost of living, which provide useful information to the market consumers.

The rest of the paper is organized as follows: Sect. 9.2 describes the literature review, while in Sect. 9.3 the theoretical background is given. Data are provided in Sect. 9.4. In Sect. 9.5, the empirical results are presented. Section 9.6 is the forecasting and finally. Summary and conclusions are provided in Sect. 9.7.

9.2 Literature Review

9.2.1 Literature Theoretical Survey

Otto Eckstein (1981) developed the concept of core inflation as the rise in the trend of household living cost due to the aggregate demand pressure in the economy.

Quah and Vahey (1995) defined core inflation as a persistent measure of headline inflation, presenting it as a medium- to long-term trend towards the headline inflation, regardless of production. The definition by Quah and Vahey has a temporary effect on price level and a non-lasting impact on the percentage of inflation.

Roger (1998) defined core inflation as a persistent and generalized component of headline inflation.

Various statistic measures such as the weighted median, the moving average, the exponential smoothing, Hodrick–Prescott filter and wavelet filter have been used in the past in order to calculate core inflation. All aforementioned measures are flexible so as to exclude the monthly differences of the data based on the extreme price movement at the specific point of time.

9.2.2 Empirical Studies of the Inflation Dynamics

Bhattacharya (2014) analysed the dynamics of inflation and monetary politics in the case of Vietnam. The study considered CPI headline inflation to be weighed against the price variations of tradable and non-tradable goods. Using VAR technique, the study estimated the inflation model.

The study by Ekong and Effiong (2015) analysed the impact of oil price shocks on Nigeria economy for the period 1986–2011. Using a two-stage approach, the study investigated the effects of variation in the supply and demand of crude oil using SVAR techniques. The results of the study suggest that the variation in aggregate supply and demand of oil goods in the local market have significant impact on macroeconomic measures such as inflation.

Gamber et al. (2015) investigated the dynamic relationship between headline and core inflation, in monetary politics for the case of CPI as well as the personal consumption expenditure deflator. More specifically, they investigated the relationship when the headline and core inflations differ and study to which extent the headline moves back to the core one and vice versa and how quickly these adjustments happen. Finally, they conclude that the dynamic relationship between the weighted median off CPI and the respective headline inflation is highly consistent across monetary policy regimes.

In her study, Priyanka Sahu (2019) compares headline and core inflation in the case of macroeconomic variables in India. The study estimates the core inflation using the conventional exclusion measure (excluding food and energy), statistic measurement of weighted median and exponential smoothing applied to monthly CPI data between January 2012 and June 2018. The findings suggest that trimming 20% of the highly volatile components from the overall inflation can serve as a better proxy for the underlying medium and long-term trend in the headline inflation.

9.3 Theoretical Background

9.3.1 ARIMA Models and the Box–Jenkins Methodology

An ARIMA model can be comprehensible by describing each of its elements as below:

Autoregression (AR): it refers to a model that presents a changing variable, which regresses to its own values with lags.
Integrated (I): it represents the difference of previous observations to allow time series to become stationary.
Moving Average (MA): it incorporates the dependence between an observation and a residual error of a moving average model, which is applied to observations with a lag.

The models of an integrated model of moving average (ARIMA) are a form of Box–Jenkins model (see Dritsaki & Dritsaki, 2020).

The ARIMA(p,d,q,) can be expressed as follows:

$$y_t = c + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} + \vartheta_1 \varepsilon_{t-1} + \cdots + \vartheta_q \varepsilon_{t-q} + \varepsilon_t \tag{9.1}$$

where

y_t is the series differentiation (first, second).
The right side of the equation above consists of the time lags of series y_t as well as the time lagged errors. This model is called the ARIMA (p,d,q) model, where.
$p =$ are the autoregression lags.
$d =$ the level of differentiation.
$q =$ are the moving average lags.

9.3.2 The Box–Jenkins Methodology

Box and Jenkins (1976) is a forecasting methodology, which applies regression studies to time series data. The methodology is based on the hypothesis that previous events affect the future ones. The models of autoregressive moving average (ARIMA) are forms of Box–Jenkins model. The Box–Jenkins approach includes the following steps:

- **Stationarity.**

The first step to develop a Box–Jenkins model is to define if the time series is stationary. Detecting stationarity is achieved through time charts, autoregression graphs as well as unit root testing.

- **Order of ARMA Model.**

Once stationarity has been dealt with, the next step is to determine the parameters of the autoregressive and moving averages, p and q, respectively. In order to determine p and q parameters, many authors are using the autocorrelation and partial autocorrelation graphs, while others are using the corrected Akaike criterion.

- **Estimating the Model's Parameters.**

The parameter estimation for Box–Jenkins models includes the arithmetic solution approach of nonlinear equations. For that reason, the econometric software EViews is being used, which has been designed to handle this approach. The estimation methods of the Box–Jenkins models are the nonlinear minimum squares and the maximum likelihood. Maximum-likelihood estimation is preferred.

- **Diagnostic Checks.**

Diagnostic tests for the Box–Jenkins models are similar to the model validation for the nonlinear adjustment of minimum squares. In other words, the error term should follow the hypothesis of a stationary process. The residuals should be a white noise or be independent (when their distributions are normal), with a constant mean and standard deviation (Ljung and Box (1978) test). Model acceptance is done with the Ramsey (1969) test.

- **Post-Sample Forecasting Accuracy.**

One use of Box–Jenkins model analysis is the forecasting. ARIMA models are based on the hypothesis that previous values of the residuals have some effect on the current or future values (Dritsaki, 2015). Once ensuring that one model is stationary and there is no problem with the diagnostic tests, we could move on with the forecasting. Forecasting estimates the return of a model in relation to real data. There is a choice to split the time series in two parts, using the first one to fit it the model and the second part to test the returns of the model. The forecasting accuracy depends on the forecasting error. The mean absolute percentage error, the square

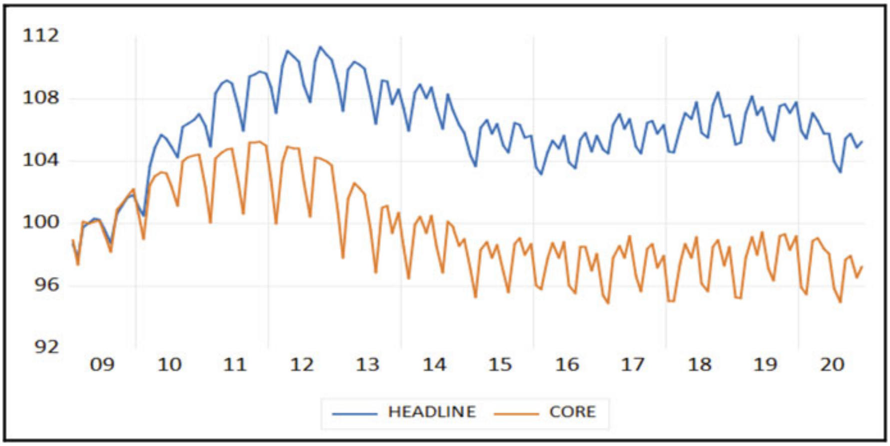


Fig. 9.1 Headline inflation vs core inflation

root of the mean-squared error and the Theil statistics are measures of accuracy whose minimum value provides us with the best fit of the model.

9.4 Data

Data used were extracted from the Hellenic Statistical Authority database source from 2009:1–2020:12. In order to smoothen out the series, data were seasonally using EViews to remove issues of seasonality.

In the following diagram, the monthly indices of headline inflation and core inflation are presented and the base year is 2009 (Fig. 9.1).

From the following diagram, we can see that headline inflation is larger than core inflation throughout the examined period showing the larger convergence after 2011 and up to 2020.

9.5 Empirical Results

9.5.1 Testing for Stationarity

- Time plots.

In the following diagram, the exponential diagram of headline inflation of Greece is presented (Fig. 9.2).

From Fig. 9.2, we can see that the log headline inflation shows an extended period of upward trend (2009–2012) followed by a fall (2012–2016) and during the period

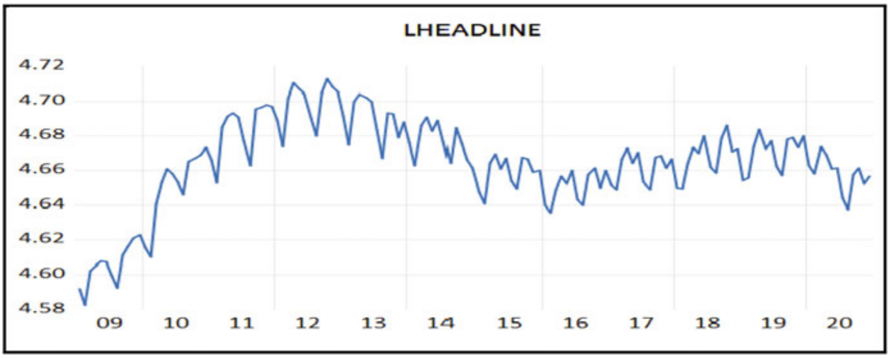


Fig. 9.2 Time series plot of log headline inflation

Dependent Variable: LHEADLINE
Method: Least Squares

Sample: 2009M01 2020M12
Included observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.657034	0.004246	1096.832	0.0000
@TREND	0.000102	5.13E-05	1.995133	$\boxed{0.0479}$

R-squared	0.027268	Mean dependent var	4.664357
Adjusted R-squared	0.020417	S.D. dependent var	0.025874
S.E. of regression	0.025608	Akaike info criterion	-4.478019
Sum squared resid	0.093121	Schwarz criterion	-4.436772
Log likelihood	324.4174	Hannan-Quinn criter.	-4.461259
F-statistic	3.980556	Durbin-Watson stat	0.228920
Prob(F-statistic)	0.047942		

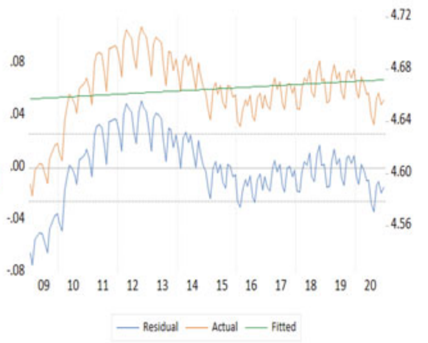


Fig. 9.3 Exponential trend model and trend analysis plot log headline inflation

2016–2020 shows a slight upward trend again. In other words, this is considered a random walk model.

- Estimation of exponential trend of series.

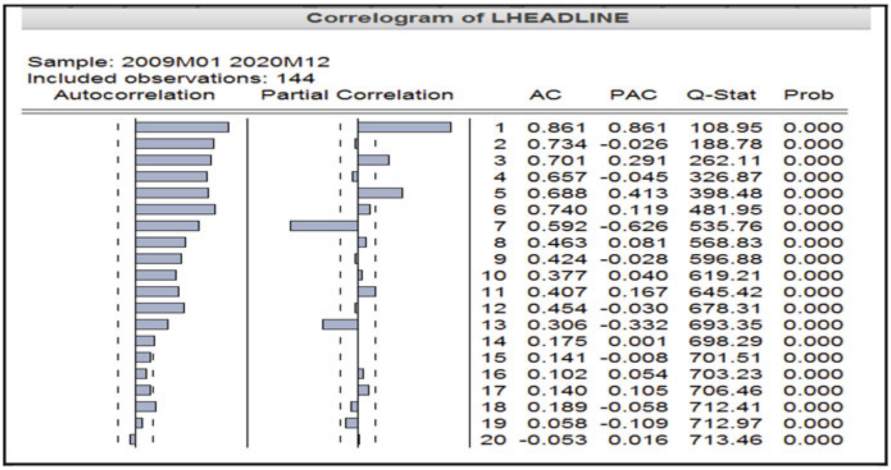
In the following figure, the estimation of exponential trend of log headline inflation together with the diagram is presented (Fig. 9.3).

The results show that there is an exponential trend of log headline inflation. Thus, we can regard the log headline inflation as a random walk model.

- Correlograms of autocorrelation coefficients.

Below on the diagram, the correlograms of autocorrelation coefficients of log headline inflation are presented (Fig. 9.4).

We can see from the above diagrams that autocorrelation coefficients decline slowly, denoting that log headline inflation is a non-stationary series.



	AC	PAC	Q-Stat	Prob
1	0.861	0.861	108.95	0.000
2	0.734	-0.026	188.78	0.000
3	0.701	0.291	262.11	0.000
4	0.657	-0.045	326.87	0.000
5	0.688	0.413	398.48	0.000
6	0.740	0.119	481.95	0.000
7	0.592	-0.626	535.76	0.000
8	0.463	0.081	568.83	0.000
9	0.424	-0.028	596.88	0.000
10	0.377	0.040	619.21	0.000
11	0.407	0.167	645.42	0.000
12	0.454	-0.030	678.31	0.000
13	0.306	-0.332	693.35	0.000
14	0.175	0.001	698.29	0.000
15	0.141	-0.008	701.51	0.000
16	0.102	0.054	703.23	0.000
17	0.140	0.105	706.46	0.000
18	0.189	-0.058	712.41	0.000
19	0.058	-0.109	712.97	0.000
20	-0.053	0.016	713.46	0.000

Fig. 9.4 Autocorrelation function log headline inflation (with 5% significance limits for the autocorrelations)

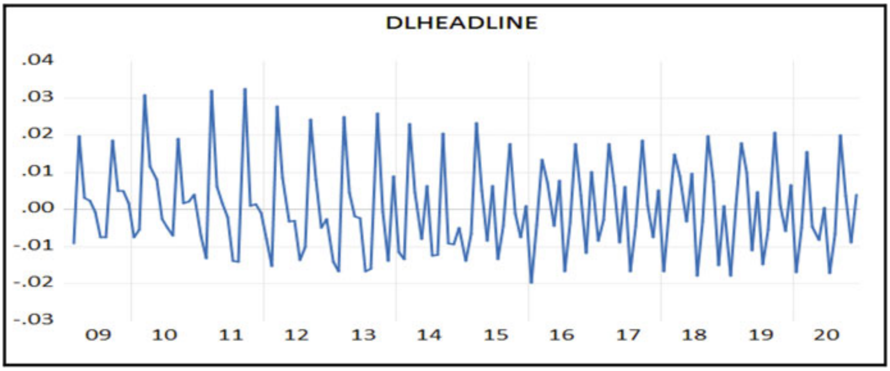


Fig. 9.5 Time series plot of log headline inflation (first differences)

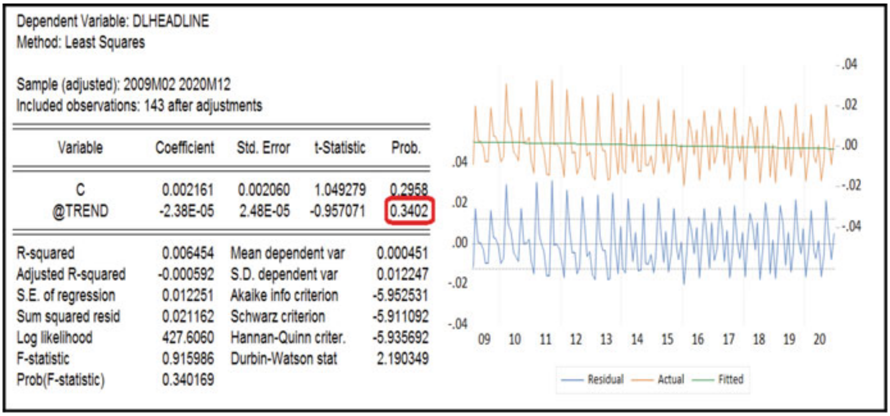
- First and second differences of series.

Afterwards, we apply anew the previous tests finding the existence of stationarity in first and second differences (Fig. 9.5).

From Fig. 9.5, we notice that the course of log headline inflation on first differences features intense fluctuations. This course is a possible evidence of mean stationarity.

In the following diagram, the estimation of exponential trend of log headline inflation in first differences is shown (Fig. 9.6).

The results of Fig. 9.6 and the table on the same figure present that there is no trend (prob. > 5%), whereas the line on the graph is horizontal in the estimated model. Thus, we conclude that the examined series is stationary.



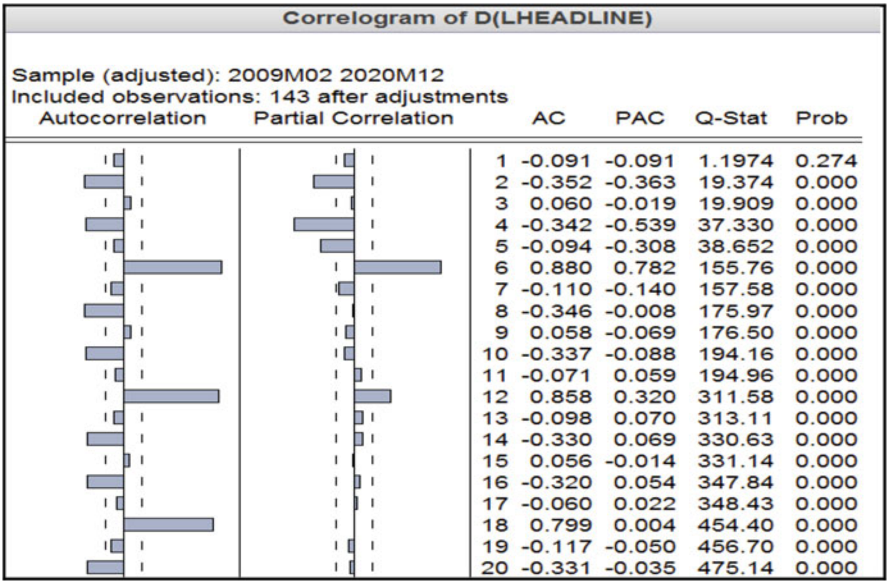
Dependent Variable: DLHEADLINE
Method: Least Squares

Sample (adjusted): 2009M02 2020M12
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002161	0.002060	1.049279	0.2958
@TREND	-2.38E-05	2.48E-05	-0.957071	0.3402

R-squared	0.006454	Mean dependent var	0.000451
Adjusted R-squared	-0.000592	S.D. dependent var	0.012247
S.E. of regression	0.012251	Akaike info criterion	-5.952531
Sum squared resid	0.021162	Schwarz criterion	-5.911092
Log likelihood	427.6060	Hannan-Quinn criter.	-5.935692
F-statistic	0.915986	Durbin-Watson stat	2.190349
Prob(F-statistic)	0.340169		

Fig. 9.6 Exponential trend model and trend analysis plot log headline inflation (first differences)



Correlogram of D(LHEADLINE)

Sample (adjusted): 2009M02 2020M12
Included observations: 143 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.091	-0.091	1.1974	0.274
		2	-0.352	-0.363	19.374	0.000
		3	0.060	-0.019	19.909	0.000
		4	-0.342	-0.539	37.330	0.000
		5	-0.094	-0.308	38.652	0.000
		6	0.880	0.782	155.76	0.000
		7	-0.110	-0.140	157.58	0.000
		8	-0.346	-0.008	175.97	0.000
		9	0.058	-0.069	176.50	0.000
		10	-0.337	-0.088	194.16	0.000
		11	-0.071	0.059	194.96	0.000
		12	0.858	0.320	311.58	0.000
		13	-0.098	0.070	313.11	0.000
		14	-0.330	0.069	330.63	0.000
		15	0.056	-0.014	331.14	0.000
		16	-0.320	0.054	347.84	0.000
		17	-0.060	0.022	348.43	0.000
		18	0.799	0.004	454.40	0.000
		19	-0.117	-0.050	456.70	0.000
		20	-0.331	-0.035	475.14	0.000

Fig. 9.7 Autocorrelation and partial autocorrelation correlograms of log headline inflation in first differences

Afterwards, we test the stationarity using the autocorrelation correlogram in first differences (Fig. 9.7).

From Fig. 9.7, we can see that the coefficients of autocorrelations decline quickly, meaning that the series is stationary.

Table 9.1 Unit root result for headline inflation

	C	C,T
L Headline	−3.239[69]**	−3.041[55]
DL Headline	−13.923[25]*	−15.505[24]*

Notes
1. * and ** show significant at 1% and 5% levels, respectively
4. Mackinnon (1996) critical value for rejection of hypothesis of unit root applied
5. The numbers within brackets followed by PP statistics represent the bandwidth selected based on Newey West (1994) method using Bartlett kernel
6. *C* constant, *T* trend
7. *D* first differences

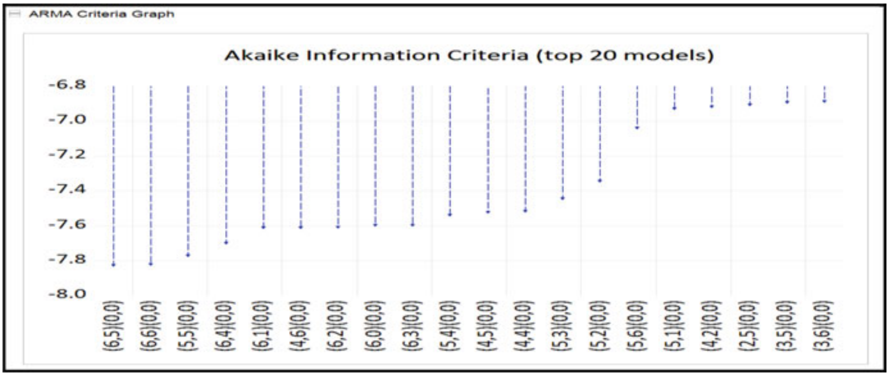


Fig. 9.8 Automatic ARIMA model estimation choice

- Unit root tests.

The confirmation of stationarity of headline inflation is employed with Phillips and Perron unit root test (1998).

The results of Table 9.1 confirm that the log headline inflation is stationary in first differences.

9.5.2 *Identification of the Model*

Using the automatic forecasting ARIMA procedure using EViews, we can find all automatic model estimations. Using the above values, we select the optimal ARMA (p,q) model among the smallest values of AIC criterion. ARMA (6,5) (0,0) model is the most suitable (Fig. 9.8).

9.5.3 Estimation and Diagnostic Tests of the Models

From the moment that the most suitable model is ARIMA (6,1,5), the estimation will be employed with maximum-likelihood approach. We maximize the likelihood by iterating Marquardt and Berndt–Hall–Hall–Hausman algorithms using derivatives, optimal step ahead and a convergence criterion for the change in the norm of the parameter vector from one iteration to the next.

The following table provides with the estimation results of ARIMA (6,1,5) model.

The results of Table 9.2 show that there is a problem in the significance of MA(5). Thus, we proceed with the ARIMA (6,1,6) model.

The results of Table 9.3 show that there is no problem in the significance of coefficients. Moreover, the estimation coefficient of error variance (volatility) $\rho_S = 1.88\mathrm{E}\text{-}05$ is also statistical significant. So, we can use the ARIMA (6,1,6) model for diagnostic testing (Table 9.4).

The test both on F distribution and also LR likelihood show that ARIMA (6,1,6) model is specified correctly (prob>5%) (Fig. 9.9).

The dotted lines in correlograms of autocorrelation and partial autocorrelations of the above diagram are approximately two standard errors, which are calculated as $\pm\frac{2}{\sqrt{n}} = \pm\frac{2}{\sqrt{144}} = \pm 0.166$. As the autocorrelation and partial autocorrelation coefficients are within these limits, we can conclude that there is independence among residuals of ARIMA (6,1,6) model in 5% level of significance (there is no autocorrelation) (Fig. 9.10).

Autocorrelation and partial autocorrelations coefficients of squared residuals are within the ± 0.166 limits; thus, we can ascertain that there is no autoregression conditional heteroscedasticity on the residuals of the ARIMA (6,1,6) model on 5% level of significance (there is no ARCH effect).

Table 9.2 Estimation of ARIMA (6,1,5) model

Dependent Variable: DLHEADLINE
Method: ARMA Maximum Likelihood (OPG - BHHH)

Sample: 2009M02 2020M12
Included observations: 143
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(6)	0.902222	0.035501	25.41390	0.0000
MA(5)	-0.148584	0.093178	-1.594634	0.1130
SIGMASQ	2.54E-05	3.00E-06	8.452534	0.0000

R-squared	0.829680	Mean dependent var	0.000451
Adjusted R-squared	0.827247	S.D. dependent var	0.012247
S.E. of regression	0.005090	Akaike info criterion	-7.630789
Sum squared resid	0.003628	Schwarz criterion	-7.568632
Log likelihood	548.6014	Hannan-Quinn criter.	-7.605531
Durbin-Watson stat	1.855988		

Inverted AR Roots	.98	.49-.85i	.49+.85i	-.49-.85i
	-.49+.85i	-.98		
Inverted MA Roots	.68	.21+.65i	.21-.65i	-.55-.40i
	-.55+.40i			

Table 9.3 Estimation of ARIMA (6,1,6) model

Dependent Variable: DLHEADLINE
Method: ARMA Maximum Likelihood (OPG - BHHH)

Sample: 2009M02 2020M12
Included observations: 143
Convergence achieved after 20 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AR(6)	0.985747	0.010183	96.80122	0.0000
MA(6)	-0.570597	0.081607	-6.992004	0.0000
SIGMASQ	1.88E-05	2.13E-06	8.840959	0.0000

R-squared	0.873696	Mean dependent var	0.000451
Adjusted R-squared	0.871892	S.D. dependent var	0.012247
S.E. of regression	0.004384	Akaike info criterion	-7.904403
Sum squared resid	0.002690	Schwarz criterion	-7.842246
Log likelihood	568.1648	Hannan-Quinn criter.	-7.879145
Durbin-Watson stat	1.894575		

Inverted AR Roots	1.00	.50+.86i	.50-.86i	-.50+.86i
	-.50-.86i	-1.00		
Inverted MA Roots	.91	.46-.79i	.46+.79i	-.46-.79i
	-.46+.79i	-.91		

Table 9.4 Ramsey RESET test

Ramsey RESET Test
Equation: UNTITLED
Omitted Variables: Squares of fitted values
Specification: DLHEADLINE AR(6) MA(6)

	Value	df	Probability
t-statistic	0.240351	139	0.8104
F-statistic	0.057769	(1, 139)	0.8104
Likelihood ratio	0.199429	1	0.6552

WARNING: the MA backcasts differ for the original and test equation. Under the null hypothesis, the impact of this difference vanishes asymptotically.

9.6 Forecasting

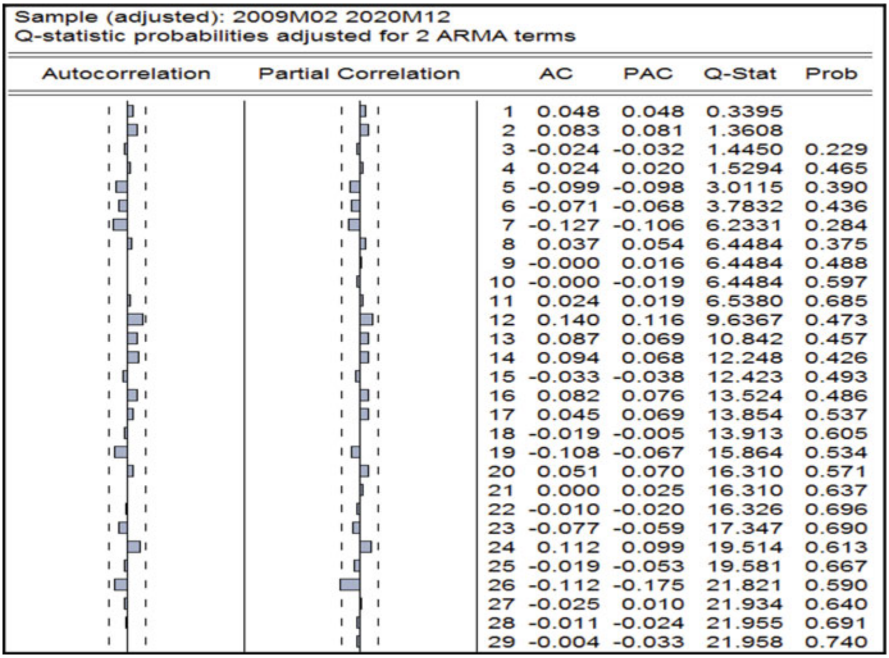
When the selected ARIMA model follows the diagnostic tests of a stationary univariate procedure, then we can use the model for forecasting.

On the following table, we present the indices of log headline inflation for the forecasting assessment of ARIMA (6,1,6) model both on dynamic and static methodologies (Table 9.5).

The results of the above table indicate that all statistical measures converge that the static forecast has the best forecast than the dynamic forecast for the ARIMA (6,1,6) model.

On the following diagram, the course of actual and forecasted values of log headline inflation of dynamic forecasting is presented (Fig. 9.11).

On the following diagram, the course of actual and forecasted values of log headline inflation of static forecasting is presented (Fig. 9.12).



Sample (adjusted): 2009M02 2020M12
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.048	0.048	0.3395	
		2	0.083	0.081	1.3608	
		3	-0.024	-0.032	1.4450	0.229
		4	0.024	0.020	1.5294	0.465
		5	-0.099	-0.098	3.0115	0.390
		6	-0.071	-0.068	3.7832	0.436
		7	-0.127	-0.106	6.2331	0.284
		8	0.037	0.054	6.4484	0.375
		9	-0.000	0.016	6.4484	0.488
		10	-0.000	-0.019	6.4484	0.597
		11	0.024	0.019	6.5380	0.685
		12	0.140	0.116	9.6367	0.473
		13	0.087	0.069	10.842	0.457
		14	0.094	0.068	12.248	0.426
		15	-0.033	-0.038	12.423	0.493
		16	0.082	0.076	13.524	0.486
		17	0.045	0.069	13.854	0.537
		18	-0.019	-0.005	13.913	0.605
		19	-0.108	-0.067	15.864	0.534
		20	0.051	0.070	16.310	0.571
		21	0.000	0.025	16.310	0.637
		22	-0.010	-0.020	16.326	0.696
		23	-0.077	-0.059	17.347	0.690
		24	0.112	0.099	19.514	0.613
		25	-0.019	-0.053	19.581	0.667
		26	-0.112	-0.175	21.821	0.590
		27	-0.025	0.010	21.934	0.640
		28	-0.011	-0.024	21.955	0.691
		29	-0.004	-0.033	21.958	0.740

Fig. 9.9 Autocorrelation and partial autocorrelation correlograms of residuals for ARIMA (6,1,6)

Table 9.5 Assessment criteria of the forecasting of ARIMA (6,1,6)

	Dynamic forecast	Static forecast
RMSE	0.0071	0.0043
MAE	0.0058	0.0034
MAPE	86.919	83.775
Theil	0.3597	**0.1858**
Bias Proportion	0.0084	0.0028
Var. Proportion	0.4843	0.0542
Cov. Proportion	0.5072	0.9428
Theil U2 coef.	0.6494	0.3144
Symmetric MAPE	102.32	62.333

9.7 Summary and Conclusion

Central Banks worldwide are mandated to maintain a stable price level for the economy. That price level is being used by each government towards the designing of monetary policies. Most of central banks make use of headline inflation towards achieving this goal. The reason is that headline inflation is a measure representing the basket of goods and services consumed by most households. However, headline inflation that is more volatile cannot be used to estimate inflation trends, hence being replaced by core inflation. Many economists suggest that whilst designing monetary

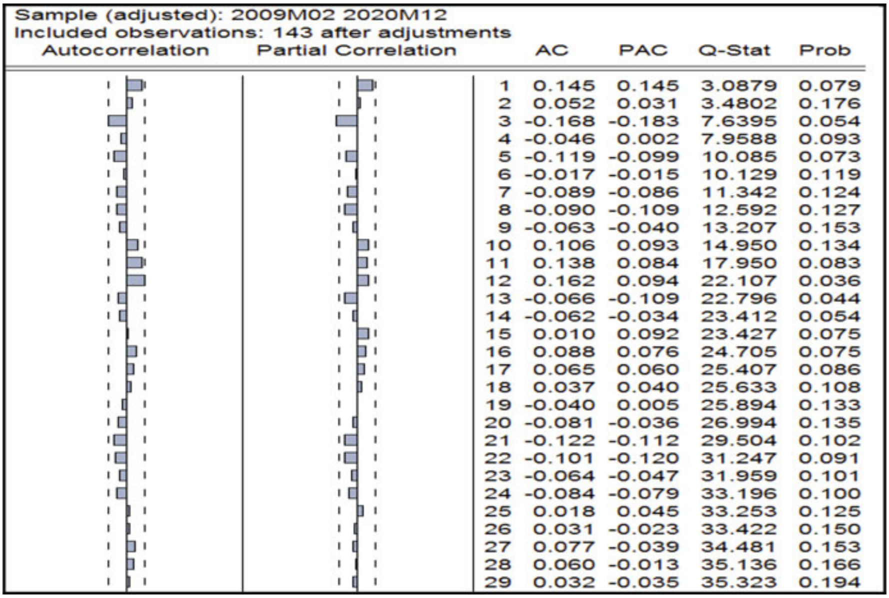


Fig. 9.10 Autocorrelation and partial autocorrelation correlograms of squared residuals for ARIMA (6,1,6)

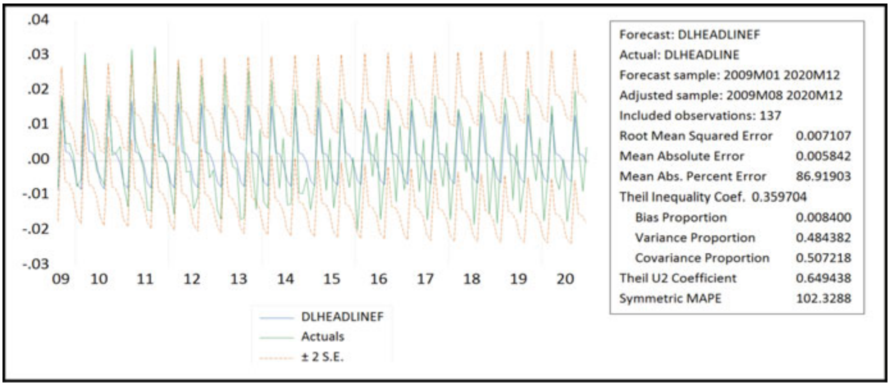


Fig. 9.11 Actual and estimated values of log headline inflation of dynamic forecasting

policies, the core inflation should be used. Their main argument is that food and energy price fluctuations and usually reported in the short run.

Despite the advantages of core inflation, their use as means of exercising monetary politics has been criticized. The measure of core inflation attempts to reduce the most volatile or transitory components of the inflation measures. But because the nature of the fluctuations can change over time, measure that has been highly volatile in the past could change in the future, to the extent that

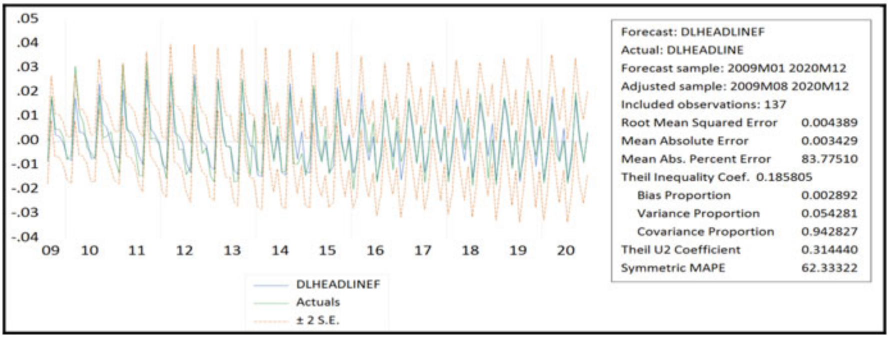


Fig. 9.12 Actual and estimated values of log headline inflation of static forecasting

any core measure could face transitory shocks. As a result, central Banks do not focus exclusively on core inflations but rather devote considerable resources into understanding the evolutions of inflation to distinguish signal from noise in the incoming data (Mishkin, 2007).

The European Central Bank has adopted the aims of inflation based on headline inflation. In contrast, USA focuses on core inflation or else the CPI. However, after the 2008 crisis, the Federal Reserve Bank considers both types of inflation when forecasting inflation.

After adopting the aims of the European Central Bank, we use headline inflation in order to forecast the inflation for Greece using monthly data from 2009:1–2020:12 and applying the Box–Jenkins methodology. The automatic model forecasting process via the Akaike criterion shows that the ARIMA(6,1,6) model is the most suitable one. The estimation of ARIMA (6,1,6) model has been achieved through the maximum-likelihood approach by iterating Marquardt και Berndt–Hall–Hall–Hausman algorithms. Moreover, in order to forecast the headline inflation on the ARIMA(6,1,6) model, both the dynamic and the static processes have been applied. The forecasting results show that static process provides better forecasting in comparison to the dynamic one.

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