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FORECASTING THE UK UNEMPLOYMENT RATE: MODEL COMPARISONS

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Abstract

This paper compares the out-of-sample forecasting accuracy of time series models using the Root Mean Square, Mean Absolute and Mean Absolute Percent Errors. We evaluate the performance of the competing models covering the period January 1971 to December 2002. The forecasting sample (January 1996 – December 2002) is divided into four sub-periods. First, for total forecasting sample, we find that MA(4)-ARCH(1) provides superior forecasts of unemployment rate. On the other hand, two forecasting samples show that the MA(4) model performs well, while both MA(1) and AR(4) prove to be the best forecasting models for the other two forecasting periods. The empirical evidence derived from our investigation suggests a close relationship between forecasting theory and labour market conditions. Our findings bring forecasting methods nearer to the realities of UK labour market.

JEL classification: C53, E27
Keywords: UK, Unemployment, Forecasting, AR, MA, GARCH

1. Introduction

A number of research papers have used time series models for forecasting macroeconomic variables. Predicting the unemployment rate is of great importance to many economic decisions. Various techniques, from the simple OLS method to the GARCH models, have been used to explain the forecasting performance of US and UK unemployment rates. Recent investigations of forecasting unemployment rate are Proietti (2001), Gil-Alana (2001), Peel and Speight (2000), Johnes (1999), Peel and Speight (1995) and Rothman (1998).

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Rothman (1998) compares the out-of-sample forecasting accuracy of six nonlinear models, while Parker and Rothman (1998) model the quarterly adjusted rate with AR(2) model. Koop and Potter (1999) use threshold autoregressive (TAR) for modelling and forecasting the US monthly unemployment rate. Recently, Proietti (2001) examines the out-of-sample forecasting for the US monthly unemployment rate by using seven forecasting models (linear and nonlinear). The study shows that linear models are characterised by higher persistence perform significantly best. As a general conclusion, Proietti (2001) argues that structural time series models are more parsimonious.

Research papers for modelling and forecasting the UK unemployment rate are Johnes (1999), Peel and Speight (2000) and Gil-Alana (2001). Johnes (1999) reports the forecasting competition between AR(4), AR(4)-GARCH(1,1), SETAR(3;4,4,4), Neural network and Naïve forecast of UK monthly unemployment rate. The sample covers the period January 1960 to August 1996. The results indicate that SETAR model dominates the others for short period forecasts, while non-linearities are present in the data.

Peel and Speight (2000) test whether nonlinear time series models of simple SETAR form are able to provide superior out-of-sample forecasts of UK unemployment data (February 1971 – September 1991). The results show evidence for superior out-of-sample SETAR forecasting performance relative to AR models (in terms of RMSE). Furthermore, Gil-Alana (2001) uses a Bloomfield exponential spectral model for modelling UK unemployment, as an alternative to the ARMA models. The results indicate that this model is a feasible way of modelling UK unemployment rate.

In this paper, we focus on modelling unemployment using data from the UK. In particular, we re-examine the evidence for forecasting by using time-series models. We compare these forecasts to several methods based on the work of recent studies.

The main purpose of this paper is to test and report the forecasting competition between different models and forecasting periods (horizons). Our approach is much in the same spirit of Proietti

(2001), Peel and Speight (2000) and Johnes (1999) in that it focuses on an in-depth comparison of forecasting models. We extend their analysis and compare the performance of twenty-three models for UK unemployment using recent data. Johnes (1999) compares five models (linear autoregressive, GARCH, threshold autoregressive and neutral network), while Proietti (2001) applies seven forecasting models for the levels of the unemployment rate. In this paper, we use the RMSE, MAE and MAPE criteria, and compare various models. For comparison purposes, we estimate different ARMA and (G)ARCH models, namely AR(p), MA(q), ARMA(p,q), GARCH(p,q), EGARCH(1,1) and TGARCH(1,1). Finally, we produce dynamic and static forecasts.

The paper is organised as follows: Section 2 provides the data and methodology, while Section 3 presents the main empirical results from various econometric models. Finally, Section 4 concludes the paper and summarises our findings.

2. Data and Methodology

We employ monthly observations of UK unemployment rate covering the period January 1971 to December 2002. The data are sourced from Datastream. The first 300 observations (January 1971 – December 1995) are used for parameter estimation, while the next 84 observations (January 1996 – December 2002) are used for forecast evaluation. Figure 1 presents the graph of the UK monthly unemployment rate series for the period January 1971 to December 2002. In the Table 1, summary statistics for unemployment rate are presented. Descriptive Statistics show a mean of six and positive values of skewness and kurtosis. Also, the Jarque-Bera statistics suggest that the normality is rejected at 5% level. ADF test fails to reject the null hypothesis of a unit root in the unemployment rate series.

Figure 1. The UK Unemployment Rate (January 1971 – December 2002)

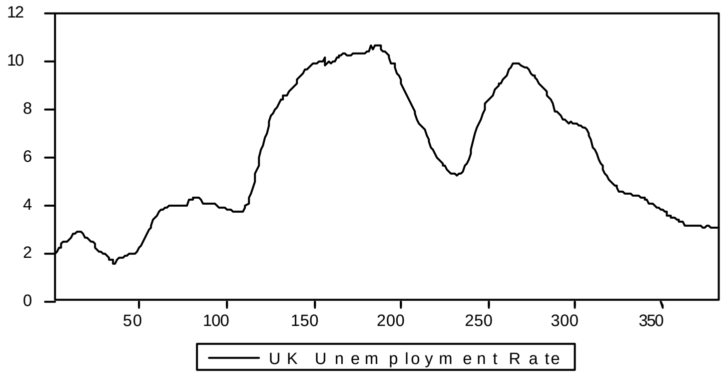

Table 1. Descriptive Statistics

	UK Unemployment Rate
Mean	6.004948
Median	5.400000
Maximum	10.60000
Minimum	1.600000
Std. Dev.	2.803374
Skewness	0.190912
Kurtosis	1.596610
Jarque-Bera	33.84470
Probability	0.000000
Observations	384
ADF- level Probability ADF- 1st diff. Probability	-1.724329 (0.4181) -3.650854 (0.0053)

The following time-series models are employed:

AR(p) model is one where the current value of a variable depends on the values that the variable took in previous periods plus an error term. AR(p) model can be expressed as:

$$Y_t = c + a_1 Y_{t-1} + a_2 Y_{t-2} + ... + a_p Y_{t-p} + u_t \qquad (1)$$

where u_t is a white noise disturbance term.

A moving average (MA) process is one in which the systematic component is a function of past innovations. MA(q) model can be expressed as:

$$Y_t = c + b_1 e_{t-1} + b_2 e_{t-2} + ... + b_p e_{t-p} + e_t \qquad (2)$$

By combining the AR(p) and MA(q) models, an ARMA(p,q) model
is a model that the current value of some series depends linearly on its own previous values plus a combination of current and previous values of a white noise error term. The ARMA(p,q) specification is given by equation (3):

$$Y_t = c + a_1 Y_{t-1} + a_2 Y_{t-2} + ... + a_p Y_{t-p} + e_t + b_1 e_{t-1} + b_2 e_{t-2} + ... + b_q e_{t-q}$$

The GARCH model of Engle (1982) and Bollerslev (1986) requires joint estimation of mean and variance equations. The current conditional variance of a time series depends on past squared residuals of the process and on past the conditional variances. The equations of GARCH(p,q) are given by:

$$Y_t = m + e_t \qquad \text{(Mean equation)}$$
$$e_t \sim N(0,1) \qquad (4)$$
$$s_t^2 = c + \sum_{i=1}^{P} a_i e_{t-i}^2 + \sum_{j=1}^{Q} b_j s_{t-j}^2 \qquad \text{(Variance Equation)}$$

The Variance equation of the Exponential- GARCH(1,1) model is given by: $\log(s_t^2) = c + a_1 \left| \frac{e_{t-1}}{s_{t-1}} \right| + a_2 \frac{e_{t-1}}{s_{t-1}} + a_3 \log(s_{t-1}^2) \qquad (5)$

The EGARCH model of Nelson (1991) captures the volatility clustering and measures the asymmetric effect. The main advantage over the GARCH model, proposed by Bollerslev (1986), is that now the leverage a_2 is exponential and variances are positive.

The Threshold-GARCH(1,1) model of Zakoian (1990) and Glosten, Jagannathan and Runkle (1993) is given by:

$$
\begin{aligned}
&Y_t = m + e_t && \text{(Mean Equation)} \\
&e_t \sim N(0,1) && (6) \\
&s_t^2 = c + a_1 e_{t-1}^2 + a_2 e_{t-1}^2 d_{t-1} + a_3 s_{t-1}^2 && \text{(Variance Equation)}
\end{aligned}
$$

Good news (e_t <0) and bad news (e_t >0) have an impact equal to a_1 and $a_1 + a_2$, respectively. In other words, a negative innovation has a greater impact than a positive innovation. The asymmetry effect is captured by the use of the dummy variable d_{t-1}.

Furthermore, we produce both dynamic and static forecasts using the selected models over the sample period. Dynamic method calculates multi-step forecasts starting from the first period in the forecast sample. Static method calculates a sequence of one-step ahead forecasts, using actual rather than forecasted values for lagged dependent variables. If S is the first observation in the forecast sample, then the dynamic forecast is given by:

$\hat{y}_s = \hat{c}(1) + \hat{c}(2)x_s + \hat{c}(3)z_s + \hat{c}(4)y_{s-1}$. On the other hand, static forecast is calculated using the actual value of the lagged endogenous variable as: $\hat{y}_{S+k} = \hat{c}(1) + \hat{c}(2)x_{S+k} + \hat{c}(3)z_{S+k} + \hat{c}(4)y_{S+k-1}$.

Following Brailsford and Faff (1996) and Johnes (1999), we compare the forecast performance of each time-series model through the error statistics (criteria). Three error statistics are employed to measure the performance of the forecasting models. Namely, the

Root Mean Squared Error (*RMSE*), the Mean Absolute Error (*MAE*), and the Mean Absolute Percent Error (*MAPE*).

Suppose that the forecast sample is $t = S, S+1,..,S+h$ and denote the actual and forecasted value in period t as y_t and $\hat{y}_t$, respectively. The reported forecast error statistics are computed as follows:

$$RMSE = \sqrt{\frac{1}{h+1}\sum_{t=S}^{S+h}(\hat{y}_t - y_t)^2}$$

$$MAE = \frac{1}{h+1}\sum_{t=S}^{S+h}\left|\hat{y}_t - y_t\right| \qquad (7)$$

$$MAPE = \frac{1}{h+1}\sum_{t=S}^{S+h}\left|\frac{\hat{y}_t - y_t}{y_t}\right|$$

The *RMSE* and *MAE* error statistics depend on the scale of the dependent variable. We use them to compare forecasts for the same series and sample across dfferent time series models. The better forecasting ability of the model is that with the smaller *RMSE* and *MAE* error statistics.

3. Empirical Results

To get a clear view and in-depth comparison of forecasting models, we divide the forecasting period (January 1996 - December 2002) into four sub-periods. The forecasting sub-periods are as follows: (i) January 1996 - September 1997, (ii) October 1997 - June 1999, (iii) July 1999 - March 2001 and (iv) April 2001 – December 2002.

We apply four forecasting models for AR(p) and MA(q) models (with p=q=1,2,3,4) using the Least Squares method, as well as four forecasting models for ARMA(p,q) (with p=q=1,2). For

GARCH(p,q), we estimate four models (p=0,1 and q=1,2) using the Marquardt algorithm. We also apply EGARCH(1,1) and TGARCH(1,1) models. Furthermore, we estimate a fourth order autoregressive/moving average model in which the residual variance is allowed to vary over time following ARCH, EGARCH and TGARCH.

Table 2 shows the selected models for each of the forecasting periods. We present the best forecasting models for UK unemployment rate (i.e. the model with the smaller forecast error statistics) using both static and dynamic methods[1].

In the case of the selected *RMSE*, the error statistics vary from 0.050920 to 1.244686. Forecasting period 2 provides the smallest *RMSE* for AR(4) model, while the largest *RMSE* is from total forecasting period for MA(4)-ARCH(1). Hence, in terms of *RMSE*, AR(4) model is the best forecasting model.

The forecasting results of the selected *MAE* measures show a minimum value of 0.040494 for forecasting period 2, and a maximum value of 0.938463 for total forecasting period. The smallest *MAE* value indicates that AR(4) model is superior than the other time series models. On the other hand, MA(4)-ARCH(1) model proves to be the worst forecasting model with the largest *MAE* value.

In the case of *MAPE*, we find that forecasting period 2 provides the smallest value (0.903837), while total forecasting period shows the largest value (19.47381). The results show that AR(4) provides superior forecasts of unemployment rate, while MA(4)-ARCH(1) model shows a poor forecasting performance.

Appendix 1 presents the parameters of the selected forecasting models. For total forecasting period, we select MA(4)-ARCH(1) as the best forecast model because it provides small *RMSE*, *MAE* and *MAPE*. For the same reason, we select AR(4) for forecasting period 2, and MA(4) for forecasting period 3 as well as forecasting period 4.

[1] The results from other models are available upon request.

For forecasting period 1, we select the MA(1) model because it provides the smallest *RMSE*. Since most of the parameters are significant at 5% level, we believe that these models can be used for potential forecasting results.

Table 2: Forecasting Performance for Selected ARMA and GARCH models

Model	RMSE	MAE	MAPE
Forecasting Period 1: January 1996-September 1997			
MA(1)- Dynamic	0.808623	0.726368	11.86642
Static	0.464449	0.414255	6.770950
MA(2)- Dynamic	0.813837	0.718821	11.29325
Static	0.271983	0.238661	3.763576
Forecasting Period 2: October 1997-June 1999			
AR(4)- Dynamic	0.076417	0.058450	1.330821
Static	0.050920	0.040494	0.903837
Forecasting Period 3: July 1999-March 2001			
MA(4)- Dynamic	0.306735	0.249912	6.605768
Static	0.222600	0.199056	5.497447
Forecasting Period 4: April 2001-December 2002			
MA(4)- Dynamic	0.199025	0.188454	5.987862
Static	0.110518	0.098961	3.143391
Forecasting Period: January 1996-December 2002			
MA(4)-ARCH(1)- Dynamic	1.244686	0.938463	19.47381
Static	0.313966	0.227025	4.677878

Furthermore, we produce static and dynamic forecasts using the selected models over the sample. Dynamic forecasting performs a multi-step forecast of unemployment rate Y, while static forecasting performs a series of one-step ahead forecasts of the dependent variable. Appendix 2 shows graphs of dynamic and static forecasts for UK unemployment rate.

4. Conclusions

Macroeconomic modelling, and forecasting, is a widely researched area in the applied economic literature. Predicting the unemployment rate is one of the most important applications for economists and policymakers. The accuracy of different forecasting methods is a topic of continuing interest and research. In this paper we report the forecasting competition between Autoregressive (AR), Moving Average (MA), GARCH, EGARCH and TGARCH models of the UK monthly unemployment rate series. We test the out-of-sample forecasting accuracy of twenty-three models. Specifically, we compare the forecasting techniques based on the following symmetric error statistics: Root Mean Square Error (*RMSE*), Mean Absolute Error (*MAE*) and Mean Absolute Percent Error (*MAPE*).

The results from the comparisons of static and dynamic forecasts by the time series models show that the simplest models are the most appropriate for forecasting. Our findings are basically as follows: (i) For total forecasting period (January 1996 – December 2002) the MA(4)-ARCH(1) model is a more appropriate approach than the other models, (ii) For forecasting period January 1996 - September 1997, the simple moving average MA(1) model produces the lowest *RMSE*. However, both *MAE* and *MAPE* suggest that MA(2) is the most appropriate model, (iii) For forecasting period October 1997 - June 1999, a fourth order linear autoregressive AR(4) is the selected forecasting model, (iv) For forecasting periods July 1999 - March 2001 and April 2001 - December 2002, we find that a fourth order moving average MA(4) model shows a good fit in our data.

The above results suggest that AR and MA models perform well in terms of forecasting, in contrast with other research papers, see Johnes (1999). One possible explanation for the forecasting superiority of these models is that traditional, simple time-series models capture the dynamical structure generating the unemployment levels. However, a highly data set is possible to affect the quality of the forecasts. In addition, forecasting results may change due to the forecasting periods (horizon) as well as the selection of in-sample and forecast data[2]. Our findings bring econometric theory nearer to the realities of UK labour market. Additional research is required to explain the forecasting superiority of simple and highly approaches

[2] The selection of the start of the forecast sample is important for dynamic forecasting.

using monthly and quarterly data. Future research should seek to investigate more complex forecasting methods to predict European and Asian unemployment series.

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Appendix 1.

I.Total Forecasting Period: January 1996 – December 2002

MA(4)-ARCH(1)				
Method: ML - ARCH (Marquardt)				
Mean Equation	Coefficient	Std. Error	z-Statistic	Prob.
c	3.913516	0.036184	108.1546*	0.0000
MA(1)	0.812872	0.014637	55.53719*	0.0000
MA(2)	0.859223	0.009520	90.25738*	0.0000
MA(3)	0.753178	0.015600	48.28041*	0.0000
MA(4)	0.853149	0.019127	44.60410*	0.0000
Variance Equation				
c	0.005592	0.001383	4.041908*	0.0001
ARCH(1)	1.229609	0.080979	15.18423*	0.0000

* Significant at the 5% level

II. Forecasting Period 1: January 1996-September 1997

MA(1)				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.329266	0.186694	33.90190*	0.0000
MA(1)	0.943030	0.024069	39.18000*	0.0000

MA(2)				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.027260	0.250451	24.06563*	0.0000
MA(1)	1.519798	0.045168	33.64772*	0.0000
MA(2)	0.825486	0.044217	18.66877*	0.0000

* Significant at the 5% level

III.Forecasting Period 2: October 1997-June 1999

AR(4)				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
c	0.021771	0.010218	2.130673*	0.0340
AR(1)	1.180820	0.063451	18.61004*	0.0000
AR(2)	0.146720	0.104039	1.410239	0.1595
AR(3)	0.048154	0.088944	0.541398	0.5886
AR(4)	-0.378836	0.050075	-7.565338*	0.0000

* Significant at the 5% level

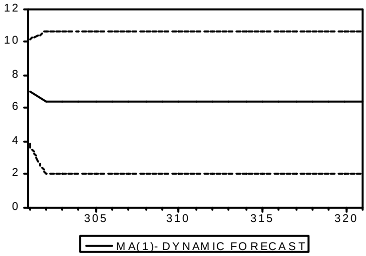
IV: Forecasting Periods: July 1999-March 2001, April 2001-December 2002

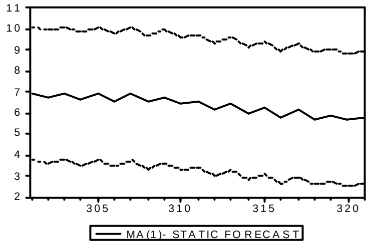
MA(4)				
Method: Least Squares				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.356913	0.516677	6.497122*	0.0000
MA(1)	2.422914	0.054966	44.08020*	0.0000
MA(2)	2.969671	0.115468	25.71847*	0.0000
MA(3)	2.150278	0.121936	17.63447*	0.0000
MA(4)	0.737983	0.060722	12.15344*	0.0000

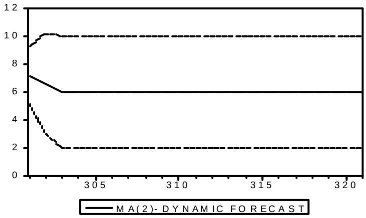
* Significant at the 5% level

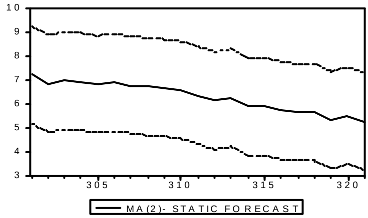
Appendix 2.
Graphs: Dynamic and Static Forecasts

- Forecasting Period 1

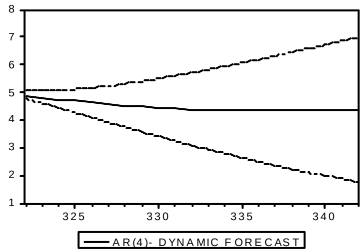


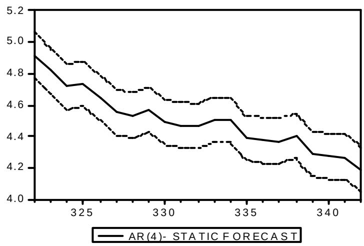






- Forecasting Period 2





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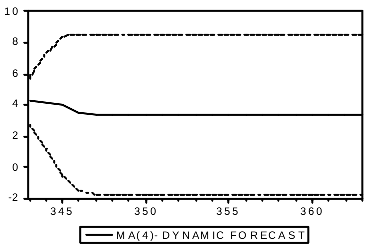
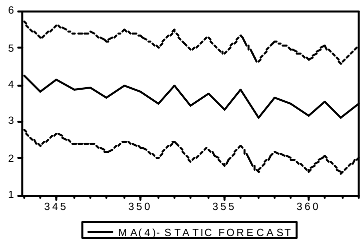
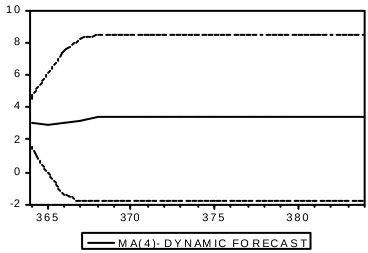
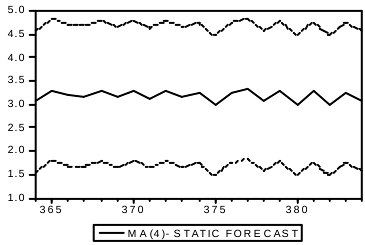


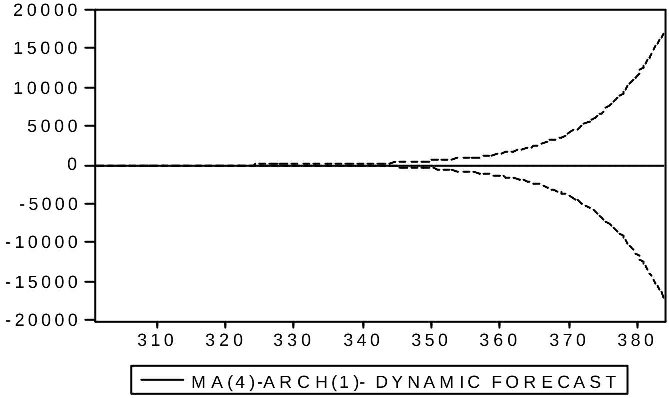


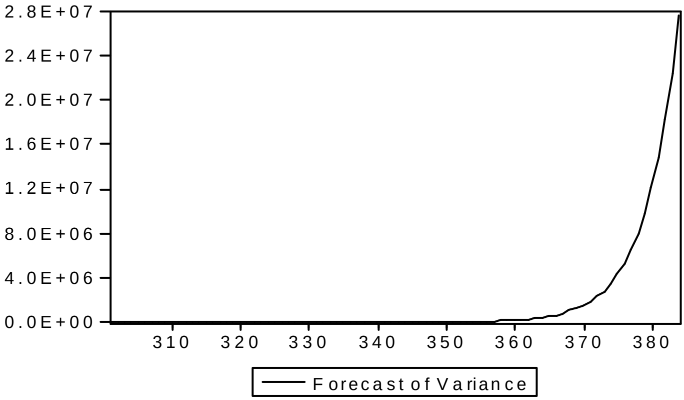
- Forecasting Period 4

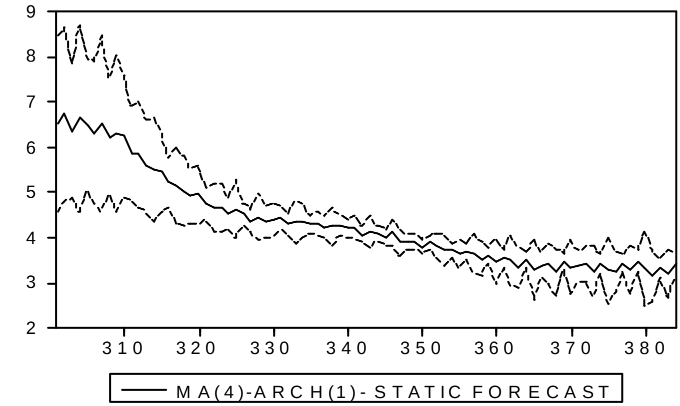




- Total Forecasting Period







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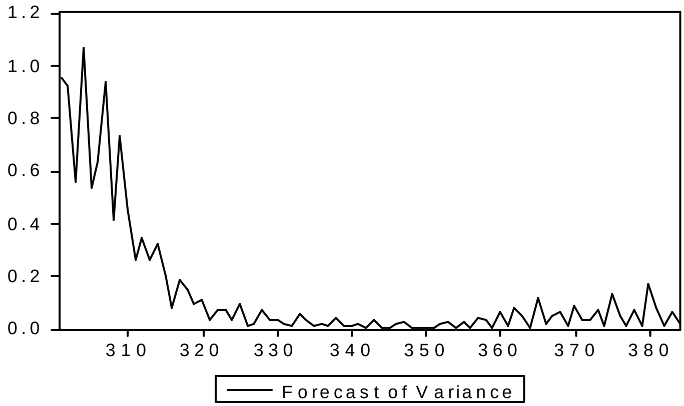
MA(4)-ARCH(1)- STATIC FORECAST



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Forecast of Variance