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Investigation of Inflation Forecasting

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Abstract: Forecasting methods of the neural network, ARIMA, ARIMA-GARCH, exponential smoothing and others are introduced. Then using U.S. inflation data, based on the out-of-sample forecasting test, the paper studies the advantages and disadvantages of these methods by the empirical comparisons. The empirical results show that, firstly, from the superior to the inferior, the ranking order of the six methods are, the ARIMA-GARCH, ARIMA, neural networks, median method of autoregressive model, least squares method of autoregressive model, exponential smoothing, no matter based on sample mean absolute error or absolute error for one-step forecasting, or absolute error for two-steps forecasting. Secondly, the ARIMA-GARCH method is suitable most to forecast the inflation level in the USA and sometimes sophisticated methods such as neural networks can not improve the forecasting results. Thirdly, according to the out-of-sample forecasting, directions of forecasting errors of these methods are almost the same, indicating that these forecasts have underestimated the inflation level in the USA.

Keywords: Inflation, Forecast, Neural Networks, ARIMA-GARCH, Exponential Smoothing.

1. Introduction

The level of inflation is an important indicator of a country's economic and financial situation. Not only national macro-management departments should pay close attention to the level of inflation, and make a reasonable and effective forecasting for the future level of inflation, and thus make arrangements in advance to macroeconomic policies, but also enterprises, individuals and other participants in financial markets, in order to make a modest investment decision, need to pay close attention to the level of inflation. So there are great significance for forecasting reasonably the level of inflation not only to national macro-management departments but also to enterprises, individuals and other participants in financial markets.

Models for forecasting inflation can be divided into two categories. The first category is the single-variable mo-//del based solely on historical data of the level of inflation. And the second category is multivariable macroeconomic model including other macroeconomic variables. As to the first category, domestic and foreign scholars mainly used GARCH, ARIMA, the median and other methods. These methods are simple, and often can achieve better predictions. Brunner and Hess (1993)[1] researched the problem of inflation forecasting using EGARCH model and state-dependent model of conditional moments. McCulloch and Jeffrey (2000) [2] caught the single order of monthly inflation in the USA using median unbiased estimate, and then constructed a stationary series of U.S. inflation using the ARMA, and forecasted inflation through the method of expanding windows and the empirical test shows that the method is better than other well-known methods. Taking use of monthly data in the form of recursive and rolling regression, Junttila (2001) [3] used the ARIMA model to test the impact of structural changes on the inflation forecasts in Finland. Nakamura (2005) [4]evaluated the effectiveness of neural networks on the inflation forecasting, and in pseudo out-of-sample forecasting experiment using American economic data, the paper shows that the neural networks model is superior to the single-variable regression model based on the mean of one and two quarters short-term level. Xiao Manjun and Xia Rongyao (2008) [5] empirical results show that the ARIMA (p, d, q) model can provide well forecasts for inflation in China. Whether

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ARIMA (p, d, q) model can be used for inflation forecasts in the United States is also a problem worth exploring.

As to the second kind of method, the Phillips curve and the quantity theory of money were frequently used. Theoretically, the second kind of method should have a better forecast due to including more economic variables. But there are two problems. First, there are many macroeconomic variables, thus which variable is exactly included is a problem. Second, if the model is used for forecast, the insurmountable problem in macroeconomic variables model is the forecast of the relevant macroeconomic variables, namely forecasting inflation using the model must forecast the relevant macroeconomic variables in the former. In fact forecasting the relevant macroeconomic variables may be more difficult than forecasting inflation. At the same time, even if the values of the relevant macroeconomic variables are gotten, the macro model needs to be steady. That is to say, the relationship between inflation and macroeconomic variables does not change as time goes by. In fact, the more variables in the model, the greater likelihood of changes in model structure may happen as time goes. Many empirical researches show that from the forecasting point of view, the univariate time series model is often no worse than the structural model including other macroeconomic variables. Cecchetti , Chu and Steindel (2000) [6] selected 19 alternative indicators from commodity prices, financial indicators and indicators of real economic situation, and constructed a simple forecasting model including each variable. In their simple statistical framework, no single indicator can be clearly and consistently to improve the forecasting effect of the autoregressive model. They found that the indicator which has good correlation with inflation, either is inherently difficult to forecast independently inflation, or have illogical inverse relationship with inflation. Their tests showed that using the indicator alone can not provide accurate signal for inflation, and in fact analysts based on the past behavior of inflation could get better predictions. Chen Yanbin, Tang Shilei, Li Du (2009) [7] showed that money supply M0, M1, and M2 have no effect on Chinese inflation, and can not forecast inflation in the short term. Binner et al (2010) [8] provided a comprehensive and sufficient evidence to determine whether the monetary aggregates are valuable in forecasting U.S. inflation, and their findings do not offer great support on the role of monetary aggregates in inflation forecasting, and instead, their results support that, the use of monetary aggregates can only lead to marginal improvement of inflation forecasting, and it is of limited value. So we use the first category, namely single-variable model only containing history data of inflations own, to forecast the inflation. Although it is called univariate model, there are many kinds when specific to the model structure and parameter estimating method. The paper prepares to select the appropriate method for forecasting U.S. inflation from a variety of univariate models, especially the method of artificial neural networks (ANNs). The artificial neural networks which are simplified simulation of biological neural networks in the human brain have the ability to learn, and they can receive training, and improve their performance through supervision or unsupervised learning [9]. Because problems of exclusive and non-linear relationship are solved, this method is widely applied to various fields. The back-propagation neural network (BPN) Rumelhart et al (1986) [10] developed is an artificial neural network using back-propagation algorithm, and it is the most representative learning model among neural networks and it has been widely used for nonlinear analysis and forecasting in many scientific and commercial fields.[9,11]. But relatively speaking, it is still relatively unusually applied to the inflation forecasting.

The rest of the paper is organized as follows. In section II we introduce several methods for forecasting U.S. inflation level, such as methods of least squares, the median of autoregressive model, exponential smoothing, ARIMA, ARIMA-GARCH and neural network, and analyze the characteristics of the sequence of U.S. inflation level by use of the figures. In section III, we give the empirical results of various forecasting methods and compare them based on forecasting for out-of-sample data. In section IV we summarize the full-text and point out the place which will be improved in the next.

2. Forecasting methods for inflation and data selection

This paper intends to use methods of least squares in autoregressive model, the median in autoregressive model, exponential smoothing, ARIMA, ARIMA-GARCH and neural network to forecast U.S. inflation. We use the year-on-year growth rate of CPI to measure the level of inflation, expressed by cpi. The paper contrasts and verifies the advantages and disadvantages of the various forecasting methods, and examines whether some relatively complex method can improve the performance of inflation forecasting through empirical research. Some simple introduction on these methods is as follows.

As to autoregressive model, we use a simple first-order form, and use the classical least squares method and the median method to estimate the parameter. The classical method for estimating model parameter is the least squares method. However in recent years the median method is becoming more popular to estimate the parameters. Quartile regression is gradually becoming an integrated approach to the linear and nonlinear responding model for statistical analysis, in part because the classical linear theory is essentially one kind of theory only for conditional expectation model [12].

Exponential smoothing includes single exponential smoothing, double exponential smoothing, Holt-Winters-Multiplicative model, Holt-Winters-Additive model and Holt-Winters-No seasonal model. On one hand, the purpose of this paper is to forecast the real level of inflation, on the other hand, the paper uses year-on-year data and thus the seasonal factors in this data have been partially eliminated. In addition, the least squares method of the autoregressive model, the median method of the autoregressive model, ARIMA, ARIMA-GARCH, and neural network methods all do not consider seasonal factors. So this paper adopts Holt-Winters-No seasonal model. Smoothed series $\hat{cpi}_t$ from series cpi_t is given as follows. [13]

$$\hat{cpi}_{t+k} = a_t + b_t k \tag{1}$$

$$a_t = \alpha \cdot cpi_t + (1-\alpha)(a_{t-1} + b_{t-1}) \tag{2}$$

$$b_t = \beta \cdot (a_t - a_{t-1}) + (1-\beta) b_{t-1} \tag{3}$$

Where cpi represents the inflation rate or the level of inflation, and $\hat{cpi}_{t+k}$ represents the estimate of cpi, and $k > 0, 0 \leq \alpha, \beta < 1$. The forecasting formula of Holt-Winters-No seasonal model is as follows. [13]

$$\hat{cpi}_{T+k} = a_T + b_T k \tag{4}$$

The ARIMA(p, d, q) estimating formula for cpi_t is as follows

$$\phi(L)\triangle^d(cpi_t) = \mu + \varphi(L)\varepsilon_t \tag{5}$$

$$\phi(L) = 1 - \phi_1 L - \phi_2 L^2 - \cdots - \phi_p L^p$$

$$\varphi(L) = 1 + \varphi_1 L + \varphi_2 L^2 + \cdots + \varphi_q L^q \tag{6}$$

In the above formula, d represents the differential number of series cpi_t, p is the autoregressive lag order, q is the moving average lag order, L is the lag operator, and ε_t is a white noise process, $L\varepsilon_t = \varepsilon_{t-1}$, $L^2\varepsilon_t = \varepsilon_{t-2}$.

In the specific empirical research, the key is to determine the value of p, d, q. The value of d depends on how many times of the difference can make the series cpi_t become a stationary series. If the series itself is stationary, then $d = 0$. The value of p and q are determined by the autocorrelation function and partial autocorrelation function of the $\Delta^d(cpi_t)$ series. In general, if the autocorrelation function of the $\Delta^d(cpi_t)$ series is trailing and the partial autocorrelation function is censoring of order p, the series can be set to the AR (p) process. If partial autocorrelation function of the $\Delta^d(cpi_t)$ series is tailing and the autocorrelation function is censoring of order q, then the series can be set to MA (q) process. If autocorrelation function and partial autocorrelation function of the $\Delta^d(cpi_t)$ series are both trailing, the series can be set to ARMA (p, q) process. On such condition, p and q can be determined through the trial way. [13, 16]

The method of ARIMA-GARCH combines GARCH method with ARIMA model. That is assuming that ε_t in formula (5) is no longer the same variance, but with varying variance h_t.

$$h_t = \omega + \Sigma_{i=1}^m \alpha_i \varepsilon_{t-i}^2 + \Sigma_{j=1}^n \beta_j h_{t-j} \tag{7}$$

Formula (7) is a GARCH(m, n) model, and GARCH(1, 1) model is frequently used in Econometric.

The previous models and methods have the specific structure. Actually it tends to have the complicated nonlinear relationship between inflation measuring factor and its lagged terms and thus using a certain specific form may not measure accurately and adequately the changing trend of inflation. Therefore, this research also used one of the most representative learning modes in the neural network: the back propagation network (BPN) to forecast the inflation rate and compare it with the other methods. Program of BPN repeatedly adjusts the connection weights in the network to minimize the gap between network real output vector and the required output vector [9, 11]. Because neural network theory is declared in detail in many literatures, this paper gave only typical three-layer architecture to explain the general idea of BPN, as shown in Fig. 1 [9, 11].

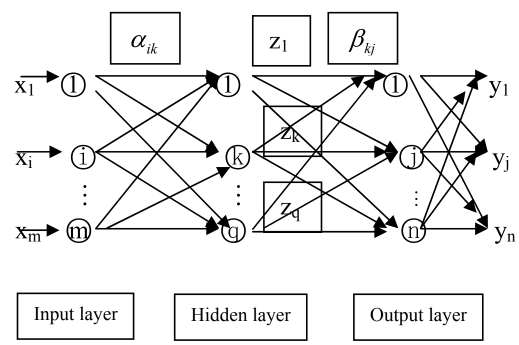

Figure 1 Structural drawing of three-layer BPN

The circles in figure 1 signify the nodes, are also called neurons. There are m nodes in the input layer, q nodes in the hidden layer, n nodes in the output layer. The nodes are linked with arrows, representing the weight of certain value. Besides, α_{ik} represents the numerical weight between the input layer and implied layer, and β_{kj} represents the numerical weight between hidden layer and output layer. [9,11]. In the specific empirical researches, the suitable weights can be selected and the appropriate networks can be gotten through the sample training and learning, and then out-of-sample data can be forecasted by use of the trained networks.

The data came from the U.S. Department of Labor, and data processing software are EViews6 and Matlab7. The data ranges from January 1990 to April 2011. From January 1990 to February 2011 is the sample interval, and the model is gotten from the interval. March 2011 to April 2011 is the verified interval of out-off-sample data, and is used to test the models forecasting ability for out-off-sample data. For the out-of-sample forecasting, dynamic forecasting is adopted in this paper, i.e., for a two-step forecasting, the former forecasting value is used rather than the actual value.

Figure 2 reflects the dynamic changing trend of U.S. inflation level from January 1990 to April 2011. The abscissa in the figure represents the time and the ordinate in

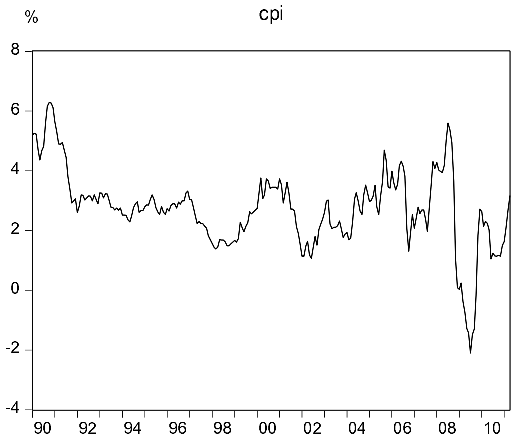

Figure 2 the Changing Characteristics of the U.S. inflation Level (From January 1990 to April 2011)

the figure represents the level of inflation. According to figure 2, we can know that the level of U.S. inflation has a downward trend in general. In 1990, the level of U.S. inflation is at historically high levels, even up to the 6.29% level. After maximum has been reached, the inflation level begins to decline, and reaches a local minimum in January 1992, and is subsequently stabilized at around 3%. The inflation level has began to decline in the end of 1996, and achieves the local low in early 1998, and subsequently begin to rise, and achieves the local high point in early 2001. Subsequently the inflation level begins to decline and achieves the local low in the mid-2002. And then there are several fluctuations of the up-down, and the inflation level achieves the local maximum value in July 2008. Followed by a sharp decline, the inflation level reaches the lowest point in the sample period by a year later. Then the inflation level gets into the rising channel and reaches 3.165% in April 2011. Overall, the level of inflation is relatively steady, and it fluctuates around the median or the mean up and down, and generally it will not deviate from the value too far. Namely when the inflation level deviates from the value, in a certain period of time, the inflation level will go back to the value by the correction mechanism.

Mean	Median	Max	Min	Std. Dev.
2.73%	2.75%	6.29%	-2.10%	1.29%
ADF				
AIC [a]	BC	HQC	Modified Akaike	Modified Schwarz
-3.798 [b] (c,0,3) [d]	-3.730 [b] (c,0,2)	-3.730 [b] (c,0,2)	-3.730 [b] (c,0,2)	-3.730 [b] (c,0,2)

Figure 3 Relevant data characteristics of the level of U.S. inflation (From January 1990 to April 2011)

[a] At the 1% significance level, the null hypothesis that the sequence of American inflation level is a unit root process is rejected, namely that the sequence of American inflation level is a stationary process.

[b] c in the parenthese indicates that unit root test including the intercept, and 0 in the parenthese indicates that unit root test not including the time trend, and 3 in the parenthese represents the lag term in the unit root test.

[d] AIC, BC, HQC, Modified Akaike and Modified Schwarz denote respectively the information criterion used to determine the optimal lag term in the unit root test.

Figure 3 shows the relevant data characteristics of the level of U.S. inflation from January 1990 to April 2011. We can know from the Figure 3 that the sequence of American inflation level is steady no matter in accordance with the standards of AIC or BC or HQC or Modified Akaike or Modified Schwarz at the 1% significant level, by using the ADF methods for unit root test.

3. Estimated results of various models and Comparison of the forecasting effect

3.1. Least-squares method of autoregressive model

$$cpi_t = 0.149588 + 0.940739 cpi_{t-1} \tag{8}$$

$$(2.46) \quad (46.8)$$

That is t value in the brackets. Its obvious that all coefficients are significant. Adjusted R-squared is 0.90, explaining that the goodness-of-fit of the equation is very good. Unit root test shows that the equation residuals are stationary. The sample mean absolute error from January 1990 to February 2011 is 0.2765%. Next, we made forecasts on future inflation according to Eq. (8). According to Eq. (8), we can predict that inflation rates in March and April 2011 are 2.1345and 2.1576% respectively. The actual values are 2.68% and 3.16% and thus the forecasting absolute error in March and April 2011 are -0.5455% and -1.0024% respectively. It is obvious that inflation levels in March and April 2011 have been underestimated.

3.2. Median method of autoregressive model

$$cpi_t = 0.122566 + 0.954436 cpi_{t-1} \tag{9}$$

$$(1.83) \quad (39.08)$$

Adjusted R-squared shows 0.69 which is less than that of least-squares method. In the perspective of goodness-of-fit, the median method of autoregressive model is not better than least squares method of autoregressive model. At the 1% significance level, the original assumptions H0: Equation residuals are nonstationary can be refused. In other words, series of equation residuals are stationary.

The sample mean absolute error from January 1990 to February 2011 is 0.2758%. According to Eq. (9), we can predict that inflation rates in March and April 2011 are 2.1364% and 2.1616% respectively. The actual values are 2.68% and 3.16% and thus the forecasting absolute error in March and April 2011 are -0.5436% and -0.9984 respectively. It is obvious that inflation levels in March and April 2011 have been underestimated.

3.3. Exponential smoothing method

We can get the estimated values of α and β according to the data. Taking them into the exponential smoothing formula, we can calculate the sample mean absolute error and the forecasting absolute error. The sample mean absolute error from January 1990 to February 2011 is 0.2759%. According to exponential smoothing method, we can predict that inflation rates in March and April 2011 are 2.0959% and 2.0818% respectively. The actual values are 2.68% and 3.16% and thus the forecasting absolute error in March and April 2011 are -0.5841% and -1.0782% respectively. It is obvious that inflation levels in March and April 2011 have been underestimated.

3.4. ARIMA method

Through tests of unit root, autocorrelation and partial correlation coefficients of the corresponding sequence, we first make sure the dynamic model of inflation level (cpi) is ARIMA(2,0,11). But there are many regressive items contained in ARIMA (2,0,11), and thus we gradually removed the regressive items with non significant coefficient using the method of from the general to the specific. Eventually we get the following ARIMA model.

$$\underset{(6.78)}{cpi_t = 2.646417} + u_t \tag{10}$$

$$u_t = \underset{(18.58)}{1.228u_{t-1}} \underset{(-5.10)}{-0.336u_{t-2}} + \underset{(13.34)}{0.502\varepsilon_t} + \underset{(2.018)}{0.061\varepsilon_{t-4}} + \underset{(13.83)}{0.542\varepsilon_{t-11}}$$

T-testing values in the brackets show that all coefficients in Eq. (10) are significant. The reciprocals of all AR root and MA root are less than 1, and this indicates that the ARIMA model is steady. Model residual sequence is also stationary. All these show that the ARIMA method is effective, so it can be used to forecast the future level of inflation in the United States. The sample mean absolute error from January 1990 to February 2011 is 0.2295%. According to the model (10), we can predict that inflation rates in March and April 2011 are 2.3293% and 2.3559% respectively. The actual values are 2.68% and 3.16% and thus the forecasting absolute error in March and April 2011 are -0.3507% and -0.8041% respectively. Apparently, inflation levels in March and April have been underestimated.

3.5. ARIMA-GARCH method

Taking GARCH effect into further consideration on the basis of Eq. (10), we finally get the mean equation as follows.

$$\underset{(8.54)}{cpi_t = 2.539873} + u_t \tag{11}$$

$$u_t = \underset{(17.45)}{1.1662u_{t-1}} \underset{(-4.20)}{-0.266u_{t-2}} + \underset{(17.13)}{0.4228\varepsilon_t} + \underset{(3.22)}{0.118\varepsilon_{t-4}} + \underset{(25.26)}{0.566\varepsilon_{t-11}}$$

The variance equation is as follows,

$$GARCH = \underset{(0.90)}{0.0008} + \underset{(2.61)}{0.1198RESID(-1)^2} + \underset{(18.82)}{0.881GARCH(-1)} \tag{12}$$

The equation residuals are stationary, and all coefficients are significant in the mean equation. The coefficients of RESID$(-1)^2$ and GARCH(-1) in the variance equation are both significant, illustrating the need to introduce GARCH effects. At the same time the F and Obs$*$ R-squared statistics for residual ARCH LM TEST show that residuals have no ARCH phenomenon, and this explains that GARCH (1,1) is enough, and no need to use the higher-order GARCH model. The reciprocals of the AR root and the MA root are less than 1, indicating that the ARIMA model is steady. According to ARIMA-GARCH method, the sample mean absolute error from January 1990 to February 2011 is 0.2286%. We can forecast the inflation rate in March and April 2011 are 2.4271% and 2.4026% respectively on the basis of the model (11-12), while the actual value is 2.68% and 3.16%. The forecasting absolute error in March and April 2011 were -0.2529% and -0.7574 %. Apparently, the levels of inflation in March and April 2011 have been underestimated.

3.6. Neural network method

The paper has adopted the BPN method with three-layer structure, and used respectively newff, newcf and newlm as generating network functions. For BPN neural network, there is an important point is that the hidden layer neuron number, and there is not a strict analytical formula to determine it. The paper uses trying methods to determine it, namely the paper selects number of neurons in the hidden layer in newff, newcf and newlm from 1 to 18 respectively, and then selects the best generating network function and the number of neurons in the hidden layer. The empirical test for the U.S. inflation data shows that when the generating network function is newlm and the number of the hidden layer neurons is 7, the trained network is the best.

According to the BPN network, the sample mean absolute error from January 1990 to February 2011 is 0.2515

%. On the basis of the training BPN neural network, we can forecast the inflation rate in March and April 2011 are 2.1771% and 2.2386% respectively, while the actual value is 2.68% and 3.16%. The forecasting absolute error in March and April 2011 are -0.5029% and -0.9214% respectively. Apparently, the levels of inflation in March and April 2011 have been underestimated by using neural network method.

4. Conclusion

In order to further compare and analyze the forecasting methods for United States inflation level, we label the results of least squares method of autoregressive model, median method of autoregressive model, exponential smoothing, ARIMA, ARIMA-GARCH and neural networks as follows, and they can be seen from Figure 4.

	sample mean absolute error	absolute error for one-step forecasting	absolute error for two-steps forecasting
least squares method of autoregressive model	0.2765%	-0.5455%	-1.0024%
Median method of autoregressive model	0.2758%	-0.5436%	-0.9984%
exponential smoothing	0.2795%	-0.5841%	-1.0782%
ARIMA	0.2295%	-0.3507%	-0.8041%
ARIMA-GARCH	0.2286%	-0.2529%	-0.7574%
neural networks	0.2515%	-0.5029%	-0.9214%

Figure 4 Forecasting effects of different methods in the sample and out of the sample

According to the Figure 4, we can get the following conclusions. Firstly, from the superior to the inferior, the ranking order of the six methods are, the ARIMA-GARCH, ARIMA, neural networks, median method of autoregressive model, least squares method of autoregressive model, exponential smoothing, no matter based on sample mean absolute error or absolute error for one-step forecasting, or absolute error for two-steps forecasting. Secondly, according to the out-of-sample forecasting, directions of forecasting errors of these methods are almost the same, and the forecasting absolute error in March and April 2011 are both negative, indicating that these predictions have underestimated the inflation level in the USA. No matter based on sample mean absolute error or absolute error for one-step forecasting, or absolute error for two-steps forecasting, the ARIMA-GARCH method is suitable most to predict the inflation level in the USA and sometimes sophisticated methods such as neural network can not improve the forecasting results. Surely this research is preliminary, and in the next researches we will apply combination forecasting and scrolling sample method to further verify the effectiveness of forecasting methods for United States inflation level.

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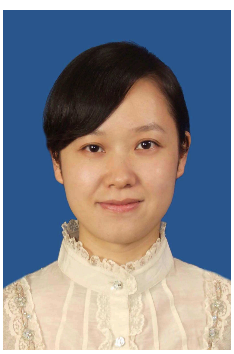

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