

Application of Consistency and Efficiency Test for Forecasts

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Abstract

The purpose of this study is to evaluate forecast efficiency by using forecast of food price inflation, consumer price index general, GDP per capita and Money supply data of Pakistan. It is therefore designed to analyze forecasting efficiency by applying consistency and efficiency criteria for annual data covering the period 1975 to 2008. Forecasts are obtained from ARIMA (auto regressive integrated moving average) model specification. Four forecasting accuracy techniques, such as, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's Inequality Coefficient (TIC) are used to be able to select the most accurate forecast model. Later on these forecasts are evaluated on the basis of consistency and Efficiency criterion defined. We found food price forecast are consistent and efficient, therefore can be used in policymaking and management decision. Forecasts test may be used before any further appliance.

Keywords: Food price Forecasts, ARIMA forecasts, Consistency test, Conditional Efficiency test.

1. Introduction

Economic theories are usually designed on the basis of econometric testing and forecast performance. Forecast performance is assumed to be providing a support for theory. This is common concept that a good forecasting performance validates the empirical model and therefore of the theory on which model are based. To take appropriate actions in future an accurate forecasting system is inevitable. It is therefore recognized that at all level in an industry one of the most important functions of a manager is planning, and planning demand a substantial need for forecasts.

Forecasting and time series analysis is not a new concept, it dated back to Yule (1927). Forecasting is often the goal of a time series analysis. Time series analysis is generally used in business and economics to investigate the dynamic structure of a process, to find the dynamic relationship between variables, to perform seasonal adjustment of economic data and to improve regression analysis when the errors are serially correlated and furthermore to produce point and interval forecast for both level and volatile data series. Accuracy of forecast is important to policymaker. Efficiency of forecast is being analyzed by different approaches; e.g Consistent Forecast, Efficient Forecast and Rational Forecasts.etc.

The aim of this study is application of different forecast accuracy test in order to get reliable forecasts. which are essential for efficient planning of industries connected to take future decisions. Such forecasts are also of interest to governments and other organizations. Our study will consist of 33 years annual data covering the period 1975-2008. We will forecast by using Box-Jenkins (ARMA). We will select a number of alternative criteria (such as, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's Inequality Coefficient (TIC)) for measuring forecast accuracy at the time of selection of best ARIMA forecasts. In order to test the forecast either they are biased, erratic and unreliable or using existing information in a reasonably effective manner we apply consistency and efficiency test of forecasts which make our study different from other. These efficiency results obtained provide no surety that a forecast best performance will be remained consistent and same for all data sets. Therefore consequences from given data set should be only considered as a exercise of forecasting evaluation and not as proof of the correctness of the underlying model and criterion for that data.

Traditional measure of forecast efficiency was comparison of RMSE. A forecast having lower RMSE considered as the best among the others forecast having a high RMSE. A good criticism on RMSE is made by Armstrong et al. (1995). After the rejection of conventional tools of analyzing the forecast efficiency the co integration approach named consistency was introduced, and this technique was used by Liu et al. (1992) and Aggerwal et al. (1995) to

assess the unbiasedness, integration and co integration characteristics of macroeconomic data and their respective forecast. Hafer *et al.* (1985), McNees (1986), Pearce (1987) and Zarnowitz (1984, 1985, 1993) place great weight on minimum mean square error (MSE) but do not incorporate accuracy analysis convincingly in their test of forecast.

Efficiency rule is defined by different researchers in different ways. In a CBO Report (1999) efficiency indicates the extent to which a particular forecast could have been improved by using additional information that was at the forecaster's disposal when the forecast was made. Nordhaus (1987) define the efficiency as ;A forecast is weakly efficient if it minimizes $E\{u_t^2|J_t\}$, where J_t is the set of all past forecasts¹ and A forecast is strongly efficient if $E\{u_t^2|I_t\}$ is minimized, where I_t is all information available at time t. Where u_t^2 is the square of forecast error at time t. This kind of efficiency perception states by Beach *et al.* (1999) that an efficient forecast incorporates all of the information available at the time the forecast is made. An efficient forecast would account for mistakes that are made on average in the current forecast. The description of a strongly efficient forecasts is one that minimizes the loss function when all information available at time t. Weak efficiency is an attractive concept, because past forecasts are likely to play a very important role in the determining the forecast errors. Nordhaus (1987) articulate the test for weak efficiency as the necessary condition for strong efficiency, or for a good forecast, but it is clearly not sufficient condition. Results of weak efficiency (50/51tests) forecast were found to be positively correlated. The degree of correlation appears to be highest for institutional forecasts (such as those made by international agencies) and lowest for professional forecasters using time-series techniques.

According to Yin-Wong *et al.* (1997) the (final) Treasury bill rate, housing starts², industrial production, inflation and most of their respective forecasts appear to be trend stationary. The corporate bond rate, GNP, the GNP deflator, unemployment and most of their respective forecasts appear to be difference stationary. About half of the unit root pairs are co integrated. The forecasts appear to behave well in response to disequilibria (defined by estimated cointegrating vectors). This finding is robust to the use of an imposed (-1 1) cointegrating vector, rather than an estimated one. In this study 30 out of 36 cases fulfill the requirement that forecast and actual possess the same order of integration. Surprisingly, the linkage between forecasts and unrevised actual series is not explicitly stronger.

The evidence from the study of Aggerwal *et al.* (1995) indicate that there are significant deviations from the rational expectations hypothesis for survey forecasts of a number of macroeconomics series. They find that survey forecasts for the consumer price index and personal income are stationary and consistent with the rational expectation hypothesis and that the surveys of housing starts, the unemployment rate and the trade balance are rational forecasts in the sense that the announced values and their survey forecasts are cointegrated. The lack of support for the rationality of survey forecasts for durable goods, industrial production, leading indicators, Money supply (M1) and retail sales suggests that the market participants are not fully exploiting either private or public information in formulating their forecasts. Study suggests the quality of forecast of industrial production and retail sales can be improved significantly by using past values. These results have important implications for decisions by many economic agents and for researchers based their studies on survey forecasts.

2. Plan of Study

We use the Box-Jenkins approach modeling ARIMA processes described in a famous book of Univariate analysis by Box *et al.* (1976). A purpose of this technique is forecasting and is widely used in time series analysis. Performance tests of forecast are based on OLS technique. After three stages of identification, estimation and diagnostic checking, we present the specification of ARIMA models to get forecasts for further application of consistency and efficiency test.

¹ This kind of efficiency notion also builds by Bakhshi *et al.* (2003) that current forecast errors should be uncorrelated with past forecast.

² Housing Starts are an important indicator of the state of the economy. Housing Starts are the number of privately owned new homes (technically housing units) that have been started over some period. Housing starts are such an important economic indicator because they show how much money the general public has. If there is a rise in housing starts it likely means there is more money in the economy.

3. Forecasts Test

After getting the forecasts we tests the performance of forecasts by

Consistent Forecast test

Efficient Forecast test

3.1 Consistent Forecast

Consistent forecast states that the, observed price series and their relevant forecast series are integrated of same order and they are cointegrated. To test the existence of unit root we follow the spirit of Dickey and fuller (1979, 1981).

According to them a series y_t is said to be stationary, if y_t follows AR (1) process. $y_t = \phi y_{t-1} + \varepsilon_t$ And the value of ϕ is less than unity. If the observed variable and their forecast are of same level of integration, say I(1). Then the first condition for consistency is met.

Concept of cointegration was first introduced by Granger (1981) and elaborates further by Engle and Granger (1987). The spirit of the cointegration in this study is that observed price series (P^o) is cointegrated with their forecast (P^e). Both series posses same order of integration, say I(1), then the linear combination³ of these two must be I(0). We define it in following way.

$$P^e_t = \Phi_1 + \Phi_2 P^o_t + \varepsilon_t \quad \varepsilon_t \approx I(0) \quad (1)$$

Where $\{\Phi_1, \Phi_2\}$ is the cointegrating vector which gives a linear of $\{P^e_t, P^o_t\}$ which is stationary. This will complete the proposition of cointegration. After that there is a need to test the stability of long run relationship through error correction mechanism.

3.1.2 Error Correction Mechanism

For the Error correction we estimate the following equations.

$$\Delta P^e_t = \alpha_1 + \alpha_2 \varepsilon_{t-1} + \sum_{i=1}^m \delta_i \Delta P^o_{t-i} + u_t \quad (2)$$

$$\Delta P^o_t = \beta_1 + \beta_2 \varepsilon_{t-1} + \sum_{i=1}^n \gamma_i \Delta P^o_{t-i} + v_t \quad (3)$$

The selection of m and n in equation 2 and 3 depends on the significance of lags under t-statistics. For a stable long run relationship between observed price index and forecast, the following feedback effect must be less than zero.

$$\alpha_2 - \Phi_2 \beta_2 < 0 \quad (4)$$

³ We used to test Granger Causality presented by Granger (1969), to make the linear combination of observed price index with their relative forecast series.

If the above condition holds, it implies that disequilibrium in previous period effects for adjustment in current time period.

3.2 Efficient Forecast

We test the efficiency hypothesis taken from the attitudes of Nordhaus (1987), Keane et al. (1990) and Bonham et al. (1995). Nordhaus (1987) define efficiency in the two classifications; weak efficiency is the necessary condition for strong efficiency, but clearly not the sufficient condition.

3.2.1 Weak efficiency

A forecast is weakly efficient if it minimizes $E\{u_t^2 | J_t\}$, where J_t is the set of all past forecasts. Where U_t^2 is the square of forecast error at time t . In order to test weak efficiency of forecasts obtained from ARIMA model, we estimate the following regression.

$$U_t^2 = \alpha_0 + \sum_{i=1}^k \alpha_i P_{t-i}^e + \varepsilon_t \quad (5)$$

Selection of k depends upon the significance under t -statistics. Only significant lags of expected food price forecasts are included and then test the weak efficiency hypothesis. Under this kind of efficiency norm, a forecast is said to be weak efficient if we are unable to reject the null that all the coefficients are simultaneously zero.

3.2.2 Strong efficiency

A forecast is strongly efficient if $E\{u_t^2 | I_t\}$ is minimized, where I_t is all information available at time t . To test the strong efficiency that depends upon the condition that the square of forecast error was not explained by the information set available at time t . As we have no information set in Univariate analysis so we regress the following equation, to test the strong efficiency for the forecasts obtained from ARIMA processes.

$$U_t^2 = \alpha_0 + \sum_{j=1}^n \alpha_j P_{t-i}^o + \varepsilon_t \quad (6)$$

Here P_t^o is the observed value of food price inflation at time t . A forecast fails to pass the strong efficiency hypothesis if α_0 and α_j are significantly different from zero.

Keane et al. (1990) and Bonham et al. (1995) test the efficiency on the basis of an extension of famous Theil-Mincer-Zarnowitz equation. This is a regression of the actual values on a constant and the forecast values. They used to add another variable from the information set available at time t , with opposing tendencies, former use a variable at level form while later use a stationary variable. Keane et al. (1990) named it conditional efficiency⁴.

⁴ Here the term conditional efficiency is different from the concept of Granger *et al.* (1973) describe conditional efficiency as combination forecast does not produce a lower RMSE then its component forecast.

3.3 Conditional Efficiency

Conditional efficiency describe by Keane et al. (1990) is based on following equation.

$$P^o_t = \alpha_o + \alpha_1 P^e_t + \alpha_2 X_{t-1} + \varepsilon_t \quad (7)$$

Here P^o_t is the observed value of food price index at time t, P^e_t is the forecast of associated price series at time t. X_t is a variable in information set at time t.

As the forecasts obtained from ARIMA processes we have no information set. P^o_{t-1} creates multicollinearity with P^e_t . Instead of lagged observed series lag of real GDP and real interest rate are used as the information available at time t. There are two reason behind this norm, first both real GDP and real interest rate reflecting the structure of the economy second Real GDP and real interest rate effectively influence the food price indices. After the estimation of equation 8 we set the following hypothesis named conditional efficiency hypothesis.

$$H_o : \alpha_o = 0, \alpha_1 = 1, \alpha_2 = 0 \quad (8)$$

Null hypothesis explained in 9 is the conditional efficiency hypothesis, a forecast is efficient upon the condition that in the existing of information set forecast fully explain the observed food price index.

Equation 8 criticized by Bonham (1995) due to incorrect integration accounting. In the following equation, the only change is the Z_t that is a stationary variable in the information set. Simply we say that $Z_t = \% \Delta X_t$.

$$P^o_t = \alpha_o + \alpha_1 P^e_t + \alpha_2 Z_{t-1} + \varepsilon_t \quad (9)$$

Now the same conditional hypothesis stated in 8 is based on equation 9 with same interpretation. According to Bonham (1995) equation 9 follows the norm of correct integration accounting.

3.4 Data Sources

In order to test the performance of Food price inflation forecast of Pakistan, we forecast four data series namely, Food price inflation (CPI food as proxy of food price inflation), consumer price index General (CPIG), Per capita Income per person (GDPI) and Money Supply(M2). The purpose of selecting these data series is their causality with each other.

All the data are taken from various issues of Economic Survey of Pakistan, Annual Reports of State Bank of Pakistan. Data are taken on annual basis for the period 1974-75, 2007-08.

4. Results and Discussions

For our data series CPIF is ARIMA(1,1,1), CPIG is ARIMA(0,1,1), GDPI is ARIMA(0,1,1) and M2 is ARIMA(0,1,1). We have to take the first difference and log to make our series stationary. We uses an iterative model building strategy that consists of selecting an initial model (model identification), estimating the model coefficients (parameter estimation) and analyzing the residuals (model checking), if necessary, the initial model is modified and the process is repeated until the residuals indicate no further modification is necessary.

Table 1.1- Specification of ARIMA Models

Variables	Food Price inflation Index	ARIMA (1,1,1)
	Consumer Price Index General	ARIMA (0,1,1)
	GDP per Capita	ARIMA (0,1,1)
	Money Supply	ARIMA (0,1,1)

Table 1.2- Forecast Statistics of Annual Data with Univariate Time Series Models

	CPIF	CPIG	GDPI	M2
Included observations	33	33	32	30
Root Mean Squared Error	2.819	2.409	3.969	3.889
Mean Absolute Error	1.744	1.448	1.949	1.933
Mean Absolute Percentage Error	3.933	3.013	3.507	3.752
Theil Inequality Coefficient	0.022	0.020	0.034	0.033
Bias Proportion	0.74%	3.75%	0.24%	0.07%
Variance Proportion	0.29%	12.52%	0.35%	0.08%
Covariance Proportion	98.97%	83.72%	99.42%	99.84%

Table 1.2 illustrates forecasts Statistics, Root Mean Squared Error (RMSE), Mean Absolute error (MAE), Mean Absolute percentage errors (MAPE), and Theil Inequality Coefficient TIC. In every case forecast error is defined as the forecast value minus the actual value, lesser will be the error better will be the forecasts. We get best forecast from our data series applying ARIMA as it is evident from statistics above.

Test of weak Efficiency criteria

To get the results for weak efficiency criteria we Regress the Square Forecast error on past Forecast, (choose the maximum lag length on the basis of significant t-statistics If neither any lag nor first lag is significant then only first lag is used) and test the weak efficiency hypothesis that no past forecast explains the square forecast error.

Square Forecast Error of CPIF Forecast

$$E1SQ = 9.387702497 - 0.02311404314 * F1(-1)$$

(0.098) (-0.146)

Square Forecast Error of CPIG Forecast

$$E2SQ = -2.109644557 - 2.001762491 * F2(-1) + 2.345809698 * F2(-2)$$

$$(-0.556) \quad (-3.711)^{***} \quad (4.120)^{***}$$

Square Forecast Error of GDPI Forecast

$$E3SQ = -16.61921239 - 9.821227468 * F3(-1) + 11.41877579 * F3(-2)$$

$$(-1.081) \quad (-2.791)^{***} \quad (3.069)^{***}$$

Square Forecast Error of M2 Forecast

$$E4SQ = -15.61391328 - 11.03425944 * F4(-1) + 12.72408534 * F4(-2)$$

$$(-1.027) \quad (-3.214)^{***} \quad (3.478)^{***}$$

For our data set no lag is significant for CPIF therefore we include first lag of forecast, whereas for CPIG, GDPI and M2 first two lags are significant and therefore used in regression.

Table1.3-Results of Weak Efficiency Hypothesis i.e Ho: All the coefficients are equal to zero

Particulars	F-statistic	Probability	Chi-square	Probability
Weak efficiency of CPIF	1.501	0.240	3.002	0.223
Weak efficiency of CPIG	11.966	0.000	35.897	0.000
Weak efficiency of GDPI	8.239	0.000	24.717	0.000
Weak efficiency of M2	8.466	0.000	25.398	0.000

Table 1.3 demonstrates the weak efficiency hypothesis result summary. CPIF only pass the test of weak efficiency criteria and indicate past forecast have considerable role in explaining the square forecast error of respective variables. Whereas CPIG, GDPI and M2 statistics represents failing of this weak efficiency criteria.

Test of Strong efficiency Criteria

In order to check the forecast for strong efficiency criteria we incorporated in the regressions that information which significantly explains the square forecast error on the basis of t-statistics. A forecast is strongly efficient if

$$E\left\{(u_t^2) | I_t\right\} \text{ is minimized, where } I_t \text{ is all information available at time } t.$$

Square Forecast Error of CPIF Forecast

$$E1SQ = 8.210465884 - 0.005186447142 * CPIF(-1),$$

$$(0.907) \quad (-0.034)$$

Square Forecast Error of CPIG Forecast

$$E2SQ = -4.132719366 + 0.2148579608 * CPIGI(-1)$$

(-0.981 (2.918)***

Square Forecast Error of GDPI Forecast

$$E3SQ = -22.7223476 + 0.9088228377 * GDPI(-1)$$

(-1.507) (3.164)***

Square Forecast Error of M2 Forecast

$$E4SQ = -19.66006956 + 0.8188586291 * M2(-1)$$

(-1.257) (2.775)***

Our regression results indicates CPIF first lag is significant at 5% level of significance in explaining the square forecast error, whereas for CPIG, GDPI, and M2 first lag is significant at 1% in explaining the square forecasts errors .Moreover, These three variable data series didnt fulfill the criteria of strong efficiency and null hypothesis acceptance probability is very low as depicted in the table1.4 below. Our CPIF is successful to pass these criteria, as passing the weak efficiency is necessary condition for a variable series to fulfill the requirements of passing the strong efficiency criteria.

Table 1.4- Results of Strong Efficiency Hypothesis i.e Ho: All the coefficients are equal to zero

Particulars	F-statistic	Probability	Chi-square	Probability
Strong efficiency of CPIF	1.501	0.240	3.003	0.223
Strong efficiency of CPIG	6.993	0.003	13.985	0.001
Strong efficiency of GDPI	6.568	0.004	13.136	0.001
Strong efficiency of M2	5.160	0.012	10.320	0.006

Conditional Efficiency Tests I

In order to get the results for conditional efficiency we regress our data series on RGDP. the statistics show a significant impact of RGDP lag on CPIF,CPIG. Where as it is insignificant in case of GDPI and M2 data series.

$$CPIF = -2.544406559 + 0.8925826442 * F1 + 3.483575237e-06 * RGDP(-1)$$

(-1.69)* (18.53)*** (2.370)*

$$CPIG = -2.318301018 + 0.8877274839 * F2 + 3.082425587e-06 * RGDP(-1)$$

(-1.420) (20.626)*** (2.083)**

$$\text{GDPI} = -2.775477421 + 0.8995176692 * F3 + 2.982395881e-06 * \text{RGDP}(-1)$$

(-1.00) (12.713)*** (1.288)

$$\text{M2} = -1.501665973 + 0.957147 * F4 + 1.397945095e-06 * \text{RGDP}(-1)$$

(-0.535) (13.799)*** (0.6032)

Table 1.5- Results of Conditional Efficiency Tests I i.e Ho: C(1)=0, C(2)=1, C(3)=0

Particulars	F-statistic	Probability	Chi-square	Probability
Conditional efficiency of CPIF	1.957	0.143	5.872	0.118
Conditional efficiency of CPIG	3.938	0.018	11.814	0.008
Conditional efficiency of GDPI	0.717	0.550	2.150	0.542
Conditional efficiency of M2	0.135	0.938	0.405	0.939

Above Table 1.5 shows the result of Conditional efficiency test given RGDP information set and surprisingly only CPIG series did not pass this criterion. Null hypothesis explained is the conditional efficiency hypothesis, a forecast for CPIF, GDPI and M2 is efficient upon the condition RGDP that in the existing information set forecast fully explain the observed food price index.

Conditional Efficiency test II

When we regress our series against Real interest rate RR, we find it has significant relationship with GDPI and Money supply.

$$\text{CPIF} = 2.3275919 + 0.9116360399 * F1 + 4.414589745e-06 * \text{RR}(-1)$$

(1.202) (12.91)*** (1.298)

$$\text{CPIG} = 1.629707318 + 0.923672918 * F2 + 2.90688348e-06 * \text{RR}(-1)$$

(1.649) (20.073)*** (1.1421)

$$\text{GDPI} = 6.486026758 + 0.569566676 * F3 + 2.223129415e-05 * \text{RR}(-1)$$

(3.444)*** (5.125)*** (3.800)***

$$\text{M2} = 6.543536054 + 0.537361573 * F4 + 2.49704145e-05 * \text{RR}(-1)$$

(3.545)*** (4.764)*** (4.119)***

Table 1.6- Results of Conditional Efficiency Tests II i.e Ho: C(1)=0, C(2)=1, C(3)=0

Particulars	F-statistic	Probability	Chi-square	Probability
Conditional efficiency of CPIF	0.637	0.597	1.911	0.591
Conditional efficiency of CPIG	2.700	0.064	8.099	0.044
Conditional efficiency of GDPI	5.046	0.006	15.137	0.002
Conditional efficiency of M2	5.679	0.003	17.036	0.001

The test of conditional efficiency in case of Real interest rate used as information set is only fulfilled by CPIF. Our statistics shows that CPIG ,GDPI and M2 forecasts are not fully explain the observed price index when other information (RR) are available in the data set.

Conclusion

The objective of this study is achieved by applying the different criterion of efficiency test. Among Our data series forecasts of food price inflation are fulfilling the efficiency criterion defined. It follows weak, strong. and conditional efficiency test for ARIMA forecasts

Table 1.6- Results Summary of ARIMA Forecasts

		1	2	2.1	2.2
Results	Food price inflation Index	1	1	1	1
	Consumer price General Index	0	0	0	0
	Per capita GDP	0	0	1	0
	Money Supply	0	0	1	0

1 for met the test, 0 otherwise

- 1 Weak Efficiency
- 2 Strong Efficiency
- 2.1 Conditional Efficiency (Real GDP)
- 2.2 Conditional Efficiency (Real Interest Rate)

We infer from our analysis that food price forecast are reliable for further application. Forecast test reduce the range of uncertainty within which management judgment can be made, so that it can be used in decision making process to the benefits of an organization and policy makers. Food Price Inflation forecasts in our data set are satisfying all the criteria used to check the performance of forecasts. We suggest policy makers and planning authorities for reliance on these criteria to get better forecasts for further appliance. If for every forecast such criterion will be used then more consistent and reliable results can be predicted.

References

- Aggarwal, R. Mohanty, S. and Song, F. (1995), "Are Survey Forecasts of Macroeconomic Variables Rational?", *Journal of Business*, 68, (1), 99-119.
- Armstrong, J. S. and Fildes R. (1995), "On the Selection of Error Measures for Comparisons among Forecasting Methods", *Journal of Forecasting*, Vol. 14, 67-71.
- Bakhshi, H., George, K. and Anthony, Y. (2003), "*Rational Expectations and Fixed-Event Forecasts: an Application to UK Inflation*", Bank of England, UK, Working Paper No. 176.
- Bonham, C. S. and Douglas, C. D. (1991), "In Search of a "Strictly Rational" Forecast", *The Review of Economics and Statistics*, Vol. 73, No. 2, 245-253.
- Bonham, C. S. and Cohen, R. (1995), "Testing the Rationality of Price Forecasts: Comment", *The American Economic Review*, Vol. 85, 284-289.
- Box, G. E. P. and G. M. Jenkins (1976), "*Time Series Analysis, Forecasting and Control*", Holden-Day, San Francisco.
- Clemen, R. T. (1989), "Combining Forecasts: A Review and Annotated Bibliography", *International Journal of Forecasting*, Vol. 5, No. 4, 559-581.
- Clement, M. P. and Hendry, D. F. (1993), "On the Limitation of Comparing Mean Square Forecast Errors", *Journal of Forecasting*, 12, 617-637.
- Clement, M. P. and Hendry, D. F. (1998), "Forecasting Economic Time Series", *Cambridge University Press*, Cambridge.
- Dickey, D. A. and Fuller, W. A. (1979), "Distribution of the Estimators for Autoregressive Time Series With a Unit Root", *Journal of the American Statistical Association*, 74, 427-431.
- Dickey, D. A. and Fuller, W. A. (1981), "Likelihood Ratio Statistics For Autoregressive Time Series With a Unit Root", *Econometrica*, 49, 1057-1072.
- Engle, R. F. and C. W. J. Granger, (1987), "Co-integration and Error Correction: Representation, Estimation and Testing", *Econometrica*, 55, 251-276.
- "Evaluating CBO's Record of Economic Forecasts", (1999), *Congressional Budget Office, Congress of the United States, Report*.
- Gavin, W. T. and Mandal, R. J. (2000), "*Forecast Inflation and Growth: do Private Forecasts Match those of Policymakers*", Federal Reserve Bank of St. Louis, Working Paper No. 026A.
- Granger, C. W. J. (1969), "Investigating Causal Relations by Econometric Models and Cross Spectral Methods", *Econometrica*, 35,
- Granger, C. W. J., (1981), "Some Properties of Time Series Data and Their Use in Econometric Model Specification", *Journal of Econometrics*, 16, 121-130.
- Government of Pakistan, *Economic survey (various issues)*, Islamabad, Ministry of Finance.
- Keane, M. P. and Runkle, D. E. (1990), "Testing the Rationality of Price Forecasts: New Evidence from Panel Data", *American Economic Review*, 80(4), 714-735.
- Keane, M. P. and Runkle, D. E. (1994), "Are Economic Forecast Rational?", Unpublished Manuscript, *Federal Reserve Bank of Minneapolis*.
- Keane, M. P. and Runkle, D. E. (1995), "Testing the Rationality of Price Forecasts: Reply", *American Economic Review*, 85, 290.