MODELING AND FORECASTING PAKISTNAN'S INFLATION BY USING TIME SERIES ARIMA MODELS

MUHAMMAD ABDUS SALAM*

SHAZIA SALAM**

METE FERIDUN***

The views expressed in this paper are not necessarily held by the Central Bank of Pakistan and are the personal responsibility of the authors. All remaining errors and omissions are of the authors.

* Statistical Officer, Statistics Department, State Bank of Pakistan, Karachi, Pakistan.
Email: muhammad.abdussalam@sbp.org.pk & salamravian@yahoo.com

** Lecturer in Statistics, Statistics Department, Government Girls College Dargai, Malakand Agency (N.W.F.P), Pakistan.
Email: shazsalam@yahoo.com

*** Lecturer in Business, Finance and Economics, Faculty of Economics and Administrative Sciences, Cyprus International University, Nicosia, Cyprus.
Email: mete.feridun@lycos.com

ACRONYMS / ABBREVIATIONS

ACF	AUTOCORRELATION FUNCTION
AIC	AKAIKE INFORMATION CRITERIA
AIC	LIKE AKAIKE INFORMATION CRITERIA
AR	AUTOREGRESSIVE
ARIMA	AUTOREGRESSIVE INTEGRATED MOVING AVERAGE
CPI	CONSUMER PRICE INDEX
DF	DICKEY FULLER
EQ CM	EQUILIBRIUM CORRECTION MODEL
E-VIEWS	ECONO-VIEW (ECONOMETRICS SOFTWARE PACKAGE)
FY	FISCAL / FINANCIAL YEAR
GARCH	GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTIC
GDP	GROSS DOMESTIC PRODUCT
H2-FY	SECOND HALF OF FINANCIAL YEAR
HRI	HOUSE RENT INDEX
IFS	INTERNATIONAL FINANCIAL STATISTICS
IMF	INTERNATIONAL MONETRY FUND
MA	MOVING AVERAGE
MAE	MEAN ABSOLUTE ERROR
OLS	ORDINARY LEAST SQUARE
PACF	PARTIAL AUTOCORRELATION FUNCTION
POL	PAKISTAN OILFIELDS LIMITED
RBI	RESERVE BANK OF INDIA
RMSE	ROOT MEAN SQUARE ERROR
RMSPE	ROOT MEAN SQUARE PERCENT ERROR
SBP	STATE BANK OF PAKISTAN
SIC	SCHWARZ INFORMATION CRITERIA
SPI	SENSITIVE PRICE INDEX
SPSS	STATISTICAL PACKAGE FOR SOCIAL SCIENCES
TIC	THEIL INEQUALITY COEFFICIENT
VAR	VECTOR AUTOREGRESSIVE
WPI	WHOLE SALE PRICE INDEX
YOY	YEAR ON YEAR BASIS

ABSTRACT

This study attempts to outline the practical steps which need to be undertaken to use autoregressive integrated moving average (ARIMA) time series models for forecasting Pakistan's inflation. A framework for ARIMA forecasting is drawn up. On the basis of in-sample and out-of-sample forecast it can be concluded that the model has sufficient predictive powers and the findings are well in line with those of other studies. Further, in this study, the main focus is to forecast the monthly inflation on short-term basis, for this purpose, different ARIMA models are used and the candid model is proposed. On the basis of various diagnostic and selection & evaluation criteria the best and accurate model is selected for the short term forecasting of inflation.

1.1 INTRODUCTION

A high and sustained economic growth in conjunction with low inflation is the central objective of macroeconomic policy. Low and stable inflation along with sustainable budget deficit, realistic exchange rate, and appropriate real interest rates are among the indicators of a stable macroeconomic environment. Thus, as an indicator of stable macroeconomic environment, the inflation rate assumes critical importance. It is therefore important that inflation rate be kept stable even when it is low. The primary focus of monetary policy, both in Pakistan and elsewhere, has traditionally been the maintenance of a low and stable rate of aggregate price inflation as defined by commonly accepted measures such as the consumer price index.

During the past three decades, dramatic changes in the inflationary environment have stimulated a wealth of studies on the relative accuracy of alternative models of inflation forecasts. Moreover, there has been much work on examining and evaluating different methodologies in forecasting inflation. One approach is associated with the work of Fama (1975, 1977) and extended by Fama and Gibbons (1982, 1984). This approach extracts from observed nominal interest rates the market's inherent expectation of inflation. Based on a univariate time-series modeling of the real interest rate, Fama and Gibbons (1984) found that the interest-rate model yields inflation forecasts with a lower error variance than a univariate model, and that the interest-rate model's forecasts dominate those calculated from the Livingston survey. Aidan Meyler, Geoff Kenny and Terry Quinn (1998) outlined ARIMA time series models for forecasting Irish inflation. It considered two alternative approaches, which suggests that ARIMA forecast has outperformed. Geoff Kenny, Aidan Meyler and Terry Quinn (1998) focused on the development of multiple time series models for forecasting Irish Inflation. The Bayesian approach to the estimation of vector autoregressive (VAR) models is employed. The results confirm the significant improvement in forecasting performance. Toshitaka Sekine (2001) estimated an inflation function and forecasts one-year ahead inflation for Japan. He found that markup relationships, excess money and the output gap are particularly relevant long-run determinants for an equilibrium correction model of inflation.

So keeping in view the above studies and literature, I have made an attempt to outline the practical steps which need to be undertaken to use autoregressive integrated moving average (ARIMA) time series models for forecasting Pakistan's inflation. A framework for ARIMA forecasting has drawn up. On the basis of in-sample and out-of-sample forecast. it has concluded that the model has sufficient predictive powers and the findings are well in line with those of other studies. This study follows simple ARIMA methodology and exclusively focuses on Pakistan and further, the main focus is to forecast the monthly inflation on short-term basis, for this purpose, different ARIMA models have used and the candid model has proposed. On the basis of various diagnostic and selection & evaluation criteria the best (candidate) models has selected for the short term forecasting of inflation.

Four different price indices are published in Pakistan: the consumer price index (CPI); calculated for four different income groups; the whole sale price index (WPI); the sensitive price index (SPI); and the Gross Domestic Product (GDP) deflator. In most countries, the main focus for assessing inflationary trends is placed on the CPI because it most closely represents the cost of living. In Pakistan, the main focus is also placed on CPI because it is used for indexation for many wages and is more relevant in measuring inflation as its impacts on households. Major developments have taken place during the recent past years as far as measurement of inflation is concerned. Not only the base year for CPI and SPI has changed from 1990-91 to 2000-01 and their coverage in terms of cities, markets, and items; weights for different commodities; income and occupational groups have also changed. They are not only more representative but include items, which are widely consumed by different income groups.

The strategy and format of this paper is as follows: Section 2 presents a purpose of CPI inflation & brief history of Pakistan's inflation. Section 3 presents brief literature review. Section 4 outlines the material & research methodology. Results and Discussion are presented in Section 5. Concluding remarks follow in Section 6.

2.1 PURPOSE OF CPI (*INFLATION*)

It seems that everywhere we look, we are reminded how good our economy is doing. And indeed, the economy is get going well, but how do the economists and econometricians really know that? Is there a simple way to gauge the economy? The answer is no! There is no simple way of figuring out how the economy is doing. There are, however, many different indicators that, once put together, can give us a rather clear picture of the economy's health. One such economic indicator is the CPI.

The CPI, calculated by the Federal Bureau of Statistics, is called an inflation indicator. Indeed, published every month, the CPI is the most important inflation indicator in the Pakistan. The way it is calculated is pretty simple, yet it serves a very important purpose. The CPI is an estimation of the price changes for a typical basket of goods. In other words, the prices of everyday goods such as housing, food, education, clothing, etc., are compared from one month to the next and the difference represents the CPI. Of course the goods are weighted appropriately in order to get an accurate measure. (For example food counts more than education since it is one of the main daily spending.) The index is calculated in relation to a base period 2000-2001 where it was set to 100. The CPI is used by the central banks when deciding the changes that need to be made to the interest rates as well as by investors when trying to predict the future price of securities. Indeed, when inflation is rising, it causes people to buy fewer goods, therefore reducing the profits of companies. This loss of profit in turns causes the company's stock prices to drop as well. This shows how important it is to monitor the CPI whether you are an individual investor or simply someone who is trying to estimate future costs and spending.

The CPI has been an important economic indicator for many years and actions related to movements in it have had direct or indirect effects on all *human beings*. It is now provide a general measure of price inflation for the household sector as a whole and is used by the central banks as the official measure of inflation for evaluating monetary policy. In the past it has been used as a starting point by parties to the national wage hearings and by the Industrial Relations Commission in determining the size and nature of wage adjustments. The CPI has also been used in recent years in the indexation of pension and superannuation payments (that is, the pension or payment is automatically adjusted, or 'indexed', using movements in the CPI). Many business contracts are regularly adjusted to take account of changes on the CPI or in some components of it. Rental agreements, insurance coverage and child support payments are frequently tied in some manner to changes in the CPI.

In short, a CPI is used for a multiplicity of purposes. Some of these are presented as:

- Compensation index; i.e., escalator for payments of various kinds;
- Cost of Living Index i.e., measure of the relative cost of achieving the same standard of living.
- Measure of changes in Consumer Prices.
- General measure of Inflation.
- Indexation of Government.
- Prices, Wages & Salary adjustments in Contracts.
- Current and Cost accounting.
- National Accounting Deflation.
- Retail rate deflation.

2.2. PAKISTAN'S INFLATION: *A BRIEF HISTORY*

Inflation rates from 1991 to 1995 have ranged between 9.25 and 12.9 percent. The high rates of monetary expansion, low rate of economic growth in three out of the five years and adjustment in administered prices contributed to the relatively high rates of inflation. Growth in international prices (in dollar terms) has been moderate or negative. Except in 1995 when price of tradable (in rupee terms) increased by 19 percent. Substantial depreciation of the exchange rate in 1990 and in 1994 also resulted in a relatively sharp increase in the price of tradable (in rupee terms) in these two years. The pressure on international reserves and an appreciation of the real exchange rate necessitated the depreciation in 1994. , The pressure on the exchange rate and reserves was caused because of the fiscal and monetary indiscipline during 1991-1993.

The period also marked a major thrust in economic liberalization of the economy. The rate of economic growth, which had flattered in 1989 and 1990, recovered strongly in the next two years. The recovery was short lived as growth rate plummeted in 1993 to its lowest level in over two decades. The growth rate improved in the next two years but is still below its historical average. The major cause for the low rate of economic growth in the last three years was natural calamities (unusual rains, floods and a virus attack on the cotton crop for three consecutive years).

The rate of monetary growth which had been brought down to 4.6 percent in 1989 climbed up to 12.6 percent in 1990 and since then has been in the region of 16 to 18 percent except in 1992 when it reached an unprecedented 30 percent. High budget deficits during these years contributed to the monetary expansion. In 1994 the rate of monetary growth was 16 percent, although budget deficit was brought down to 5.8 percent of the GDP. The growth in money supply in 1994 was mainly on account of accumulation of net foreign assets rather than domestic credit creation. As mentioned above, the build up of foreign reserves had become necessary because of a draw down of reserves in the previous years. Thus the reasons for the increase in money supply in 1994 were qualitatively very different from those in the previous three years.

Pakistan has experienced sustained inflation hovering between 10.0 to 13.0 percent range during the first eight years of the 1990s. Not surprisingly, one of the thorniest issues in Pakistan's policy arena during those periods has been how to put inflation under effective control The persistence of a double-digit inflation along with large fiscal deficit (7.0% of GDP) have been the major source of macroeconomic imbalances in the 1990s. There has been a general agreement that the excessive growth in money supply, the supply side bottlenecks, the adjustment in government – administered prices, the imported inflation (pass through of exchange rate adjustment), escalations in indirect taxes, and inflationary expectations has the major factors responsible for the persistence of a double-digit inflation during most periods of the 1990s. Both food and non-food inflation contributed to the persistence of the double-digit inflation. Food and non-food inflation averaged 11.6 percent and 10.3 percent, respectively during the eight years of the 1990s. Inflation slowed to an average of 4.7 percent in the remaining two years of the 1990s, mainly on account of 4.1 percent food inflation and 5.3 percent non-food inflation. Non-food inflation was mainly driven by the prices of Pakistan Oilfields Limited (POL) products and rise in transport charges. Inflationary pressures have continued to diminish over the last three years mainly on account of tight monetary policy, prudent fiscal management, and improved supply of food items in the country. Although the exchange rate adjustments and the rise in international price of POL products have put upward pressures on inflation but these pressures were countered by the tight monetary policy fully supported by fiscal stance and improvement in the supply situation in the country. During the last three years (1999-00 to 2001-02) overall inflation averaged 3.5 percent as against double-digit inflation during most periods of the 1990s. As stated earlier the decline in overall inflation owe heavily to low (2.4%) food inflation, as non-food inflation averaged 5.1 percent during the last three years. There is no room for complacency; however there seems to be grounds for optimism with respect to the chances of safeguarding the progress that has been achieved on the inflation front over the last three years. Inflationary pressures dampened considerably during Fiscal / Financial Year 2002 (FY02) despite the aftermath of events of September 11 and continuation of a drought-like situation in the country. Better availability of essential commodities, due to improved production of food and non-food items as well as the food stocks for prior periods, had a moderating influence on inflation.

Inflation has further decelerated during FY03, to 3.1 percent compared to 3.5 percent in FY02. While both food and non-food components of inflation saw a visible decline during FY03, it was the former that witnessed a sharper fall. Improved availability of majority of essential food items, imported deflation and cheap availability of credit seem to be the key factors that curtailed inflation in FY03. However, there has been a mixed trend in the annual inflation pattern when viewed by the changes in the price indices other than the CPI. WPI recorded an annual increase of 5.9 percent in FY03 as compared to 2.1 percent last year. Similarly, SPI though recorded a subdued rate of increase of 3.5 percent during FY03 but marginally higher than the 3.4 percent increase recorded during FY02. However, in WPI, the marginal rate declined steadily through H2-FY03.

After bottoming out at all-time low of 1.4 percent in July 2003, marginal (YoY) CPI inflation witnessed a steep rise through most of FY04 to close at 8.5 percent, taking the average CPI inflation for the year to 4.6 percent. While the rise in domestic CPI inflation was indeed influenced by international prices, the impact of these was mitigated, to an extent, through fiscal measures.6 As a result, in contrast to trends in most regional economies, the rise in Pakistan's CPI inflation during FY04 largely stemmed from domestic sources, reflected principally in the leading roles of the food and house rent sub-groups respectively. The CPI food inflation witnessed a sharp rise of 13.4 percent (YoY) in June 2004 as compared to a quite subdued 0.9 percent in June 2003, taking annualized food inflation to 6.0 percent for FY04. The acceleration in CPI food inflation, October 2003 onwards, was largely attributed to artificial supply shortages of wheat that were probably due to the realization that Government's capacity to intervene was hampered by depleted wheat reserves. On the other hand, CPI non-food sub-group witnessed a YoY increase of 5.3 percent in June 2004, while annualized non-food inflation recorded a rise of 3.6 percent in FY04. CPI non-food inflation was quite benign before setting for an upward trend in March 2004 onward. The rising pressures mainly stemmed from sub-group of house rent index (HRI). The role of HRI was critical in accelerating the overall CPI inflation, as this component has a 23.43 percent weight in the CPI basket. Specifically, HRI rose by 8.2 percent on year-on-year basis in June 2004 compared with only 1.2 percent in June 2003.

3. LITERATURE REVIEW

Numerous studies have investigated the relative accuracy of alternative inflation forecasting models. One approach has been to compare the accuracy of survey respondents' inflation forecasts relative to univariate time-series models. Another approach is the methodology associated with the work of Fama (1975, 1977) and recently extended by Fama and Gibbons (1982, 1984). This approach extracts from observed nominal interest rates the market's inherent expectation of inflation. Based on a univariate time-series modeling of the real interest rate, Fama and Gibbons (1984) find that the interest-rate model yields inflation forecasts with a lower error variance than a univariate model, and that the interest-rate model's forecasts dominate those calculated from the Livingston survey.

Aidan Meyler, Geoff Kenny and Terry Quinn (1998) outlined autoregressive integrated moving average (ARIMA) time series models for forecasting Irish inflation. It considered two alternative approaches to the issue of identifying ARIMA models - the Box Jenkins approach and the objective penalty function methods. The emphasis is on forecast performance, which suggests that ARIMA forecast has outperformed.

Geoff Kenny, Aidan Meyler and Terry Quinn (1998) focused on the development of multiple time series models for forecasting Irish Inflation. The Bayesian approach to the estimation of vector autoregressive (VAR) models is employed. This allows the estimated models combine the evidence in the data with any prior information, which may also be available. A large selection of inflation indicators is assessed as potential candidates for inclusion in a VAR. The results confirm the significant improvement in forecasting performance, which can be obtained by the use of Bayesian techniques.

Toshitaka Sekine (2001) estimated an inflation function and forecasts one-year ahead inflation for Japan. He found that markup relationships, excess money and the output gap are particularly relevant long-run determinants for an equilibrium correction model (Eq CM) of inflation

Tim Callen and Dongkoo Chang [1999] found that the Reserve Bank of India (RBI) has moved away from a broad money target toward a "multiple indicators" approach to the conduct of monetary policy. In adopting such a framework, it is necessary to know which of the many potential indicators provide the most reliable and timely information on future developments in the target variable(s). This paper assesses which indicators provide the most useful information about future inflationary trends. It concludes that while the broad money target has been de emphasized, developments in the monetary aggregates remain an important indicator of future inflation. The exchange rate and import prices are also relevant, particularly for inflation in the manufacturing sector. Maintaining a reasonable degree of price stability while ensuring an adequate expansion of credit to assist economic growth have been the primary goals of monetary policy in India (Rangarajan, 1998). The concern with inflation emanates not only from the need to maintain overall macroeconomic stability, but also from the fact that inflation hits the poor particularly hard as they do not possess effective inflation hedges. One may say that Inflation is the single biggest enemy of the poor. Consequently, maintaining low inflation is seen as a necessary part of an effective anti-poverty strategy. By the standards of many developing countries, India has been reasonably successful in maintaining an acceptable rate of inflation. Since the early 1980s inflation has not exceeded 17 percent (measured by the year-one-year change in the monthly WPI and has averaged about 8 percent. While this is only on par with other countries in the Asian region,

Francisco Nadal-De Simone (2000) estimated two time-varying parameter models of Chilean inflation Box-Jenkins models outperform the two models for short-term out-of-sample forecasts; their superiority deteriorates in longer forecasts.

Aidan Meyler, Geoff Kenny and Terry Quinn (1998) have considered autoregressive integrated moving average (ARIMA) forecasting. ARIMA models are theoretically justified and can be surprisingly robust with respect to alternative (multivariate) modeling approaches. Indeed, Stockton and Glassman (1987, pg. 117) upon finding similar results for the United States commented that "it seems somewhat distressing that a simple ARIMA model of inflation should turn in such a respectable forecast performance relative to the theoretically based specifications."

Ling and Li (1997) considered fractionally integrated autoregressive moving-average time series models with conditional heteroscedasticity, which combined the popular generalized autoregressive conditional heteroscedastic (GARCH) and the fractional (ARMA) models. Drost and Klaassen (1997) said that it is well-known that financial data sets exhibit conditional hereroskedasticity. GARCH-type models are often used to model this phenomenon. They constructed adaptive and hence efficient estimators in a general GARCH in mean-type context including integrated GARCH models.

4. MATERIALS AND RESEARCH METHODOLOGY

A modeling and forecasting of various ARIMA time series models based on Pakistan's monthly Inflation data would be carried out.
To realize the objectives of the study, the following steps will be taken in this regard:

1. Collection of monthly inflation data from the secondary sources like Pakistan Economic Survey, State Bank of Pakistan and International Financial Statistics (IFS), the IMF publication.
2. Specification and estimation of various possible types of ARIMA models.
3. Obtaining of ex-post forecast after empirically estimating the various types of ARIMA models.
4. Comparison of forecasting performance of various types of ARIMA models by using certain statistical measures.

It is a research study on inflation monthly data based on CPI, which have been collected for the period from July1993 to June 2004, and then ex-post twelve months ahead (one year) forecasts for inflation would be carried out. The E-VIEWS, SPSS and Excel as the main statistical software's for estimation purpose have been employed. The research will be conducted in four stages, a detail of which is give as under:

In the first phase, the statistical properties/summary statistics as well as distribution of all time series will be tested by means of coefficient of skewness and kurtosis, normal probability plots and Jarque-Bera test of normality, to check presence of typical stylized facts.

In second phase, time series will then be tested for stationarity both graphically and with formal testing schemes by means of autocorrelation function, partial autocorrelation function and using Augmented Dickey-Fuller test of unit root. If the original or differenced series comes out to be non-stationary some appropriate transformations will be made for achieving stationarity, otherwise we will proceed to next phase.

In third phase, based on Box-Jenkins methodology, an appropriate model(s), which best describes the temporal dependence in the inflation series, will be identified using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) and estimated via Ordinary Least Square (OLS) method. Estimated model(s) will be considered most appropriate if it typically simulate historical behavior as well as constitute white-noise innovations. The former will be tested by ACF and PACF of estimated series while the latter will be tested by a battery of diagnostic tests based on estimated residuals as well as by over-fitting. The best fitting model(s) will then go under various residual and normality tests and only qualifying model(s) will be selected and reserved for forecasting purpose.

Finally, Forecasting performance of the various types of ARIMA models would be compare by computing statistics like Akaike Information Criteria (AIC), Schwarz Information Criteria (SIC), Theil Inequality Coefficient (TIC), Root Mean Square Error (RMSE), Root Mean Square Percent Error (RMSPE), Mean Absolute Error (MAE). On the basis of these aforementioned selection & evaluation criteria concluding remarks have been drawn.

A detailed methodology would be carried out, which we mention here for subsequent analysis:

The study focuses on the Box-Jenkins (1976) approach to identification, estimation, diagnostic checking, and forecasting a univariate time series. ARMA models can be viewed as a special class of linear stochastic difference equations. By definition, an ARMA model is covariance stationary in that it has a finite and time-invariant mean and covariance. For an ARMA model to be stationary, the characteristic roots of the difference equation must lie inside the unit circle. Moreover, the process must have started infinitely far in the past or the process must always be in equilibrium.

In the identification stage, the series is plotted and the sample autocorrelations and partial correlations are examined. As illustrated using the CPI inflation data, a slowly decaying autocorrelation function suggests nonstationarity behavior. In such a circumstances. Box and Jenkins recommend differencing the data. A common practice is to use a logarithmic or Box-Cox transformation if the variance does not appear to be constant. We present some modern techniques that can be used to model the variance. The sample autocorrelations and partial correlations of the suitably transformed data are compared to those of various theoretical ARMA processes. All plausible models are estimated and compared using a battery of diagnostic criteria. A well estimated model (1) is parsimonious; (2) has coefficients that imply stationarity and invertibility; (3) fits the data well (4) has residuals that approximate a white-noise process; (5) has coefficients that do not change over the sample period; and (6) has good out-of-sample forecasts. The most parsimonious model may not have the best fit or out-of-sample forecasts. You will find yourself addressing the following types of questions: What is the most appropriate data transformation? Is an ARIMA (2, 1) model more appropriate than an ARMA (1, 2) specification? How to best model seasonally? Given this latitude, many view the Box-Jenkins methodology as an art rather than a science. Nevertheless, the technique is best learned through experience.

In finite samples, the correlogram of a unit root process will decay slowly. As such, a slowly decaying ACF can be indicative of a unit root or near unit root process. The issue is especially important since many economic time series appear to have a non-stationary component. When we encounter such a time series, do we detrend, do we first-difference, or do we do nothing, since the series might be stationary? Adherents of the Box-Jenkins methodology recommend differencing a nonstationary variable or variable with a near unit root. For very short-term forecasts, the form of the trend is nonessential. Differencing also reveals the pattern of the other autoregressive and moving average coefficients. However, as the forecast horizon expands, the precise form of the trend becomes increasingly important. Stationarity implies the absence of a trend and long-run mean reversion. A deterministic trend implies steady increases (or decreases) into the infinite future. Forecasts of a series with a stochastic trend converge to a steady level.

The usual t-statistics and F-statistics are not applicable to determine whether or not a sequence has a unit root. Dickey and Fuller (1979, 1981) provide the appropriate test statistics to determine whether a series contains a unit root, unit root plus drift, and/or unit root plus drift plus a time trend- The tests can also be modified to account for seasonal unit roots- If the residuals of a unit root process are heterogeneous or monthly dependent, the alternative Phillips-Perron test can be used. Structural breaks will bias the Dickey-Fuller and Phillips-Perron tests toward the non-rejection of a unit root. Perron (1989) shows how it is possible to incorporate a known structural change into the tests for unit roots. Caution needs to be exercised since it is always possible to argue that structural change has occurred; each year has something different about it than the previous year. In an interesting extension, Perron and Vogelsang (1992) show how to test for a unit root when the precise date of the structural break is unknown. All the aforementioned tests have very low power to distinguish between a unit root and near unit root process.

It is important to note, however, that this process is not a simple sequential one, but can involve iterative loops depending on results obtained at the diagnostic and forecasting stages. The first step is to collect and examine graphically and statistically the data to be forecast. The second step is to test whether the data are stationary or if differencing is required. Once the data are rendered stationary one should seek to identify and estimate the correct ARMA model.

We would be using the standard Box-Jenkins methodology for model identification. It is important that any identified model be subject to a number of diagnostic checks (usually based on checking the residuals). If the diagnostic checks indicate problems with the identified model one should return to the model identification stage. Once a model or selection of models has been chosen; the stability of the estimated parameters should be tested with respect to time frame chosen. The estimated parameters should be robust with respect to the time frame. The models should then be used to forecast the time series, preferably using out-of-sample data to evaluate the forecasting performance of the model. It is pertinent to mention that one common pitfall of ARIMA modeling is to over fit the model at the identification stage, which maximizes the in-sample explanatory performance of the model but may lead to poor out-of-sample predictive power relative to a more parsimonious model. Thus, if a model with a large number of AR and MA lags yields poor forecasting performance, it may be optimal to return to the model identification stage and consider a more parsimonious model.

5. RESULTS AND DISCUSSION

5.1 DATA COLLECTION AND EXAMINATION

A lengthy time series data is required for univariate time series forecasting. It is usually recommended that at least 50 observations be available (see for example, Meyler, A, G. Kenny and T. Quinn (1998)). Using Box-Jenkins methods can be problematic if too few observations are available. Unfortunately, even if a long time series is available, it is possible that the series contains a structural break, which may necessitate only examining a sub-section of the entire data series, or alternatively using intervention analysis or dummy variables. Thus, there may be some conflict between the need for sufficient degrees of freedom for statistical robustness and having a shorter data sample to avoid structural breaks. Graphically examining the data is important. They should be examined in levels, logs, differences and log differences. The series should be plotted against time to assess whether any structural breaks, outliers or data errors occur. If so one may need to consider use of intervention or dummy variables. This step may also reveal whether there is a significant seasonal pattern in the time series. Consider, for example, a plot of the first difference of the log of the CPI series for the period July 1993 through June 2004 as shown in Figure 1.1 & 1.2. From the figure 1.2 and summary table 1, it is evident that for the period Jul-1993 to Mar-1997, the mean rate of, and standard deviation of, inflation was 11.6 and 1.5 respectively, which indicates that inflation was in double digit and remained consistent throughout the period. After March, 1997 the rate of inflation was showing downward trend with an average inflation of 8.1 and that of standard deviation was 2.7. This high value of standard deviation claim that there is almost double variation for the period Apr-1997 to Jan-1999 due to this decaying process, then from Feb-1999 to Jul-2003, the inflation was getting smoothen and stable with an average rate of 3.5 and standard deviation 1.1. After this era, the inflation was getting climbing to an almost double standard deviation 2.0 as compared to previous era with an average of 4.9. These four phases of graphical depiction of inflation gives visual clue of non-stationarity.

Table 1: Summary Statistics for Pakistan's Monthly Inflation

Period	Average	Standard Deviation
Jul-1993 to Mar-1997	11.6	1.5
Apr-1997 to Jan-1999	8.1	2.7
Feb-1999 to Jul-2003	3.5	1.1
Aug-2003 to Jun-2004	4.9	2.0
Overall Period (July 1993 to June 2004)	**7.2**	**4.0**

Another way to examine the properties of a time series is to plot its autocorrelogram. The autocorrelogram plots the autocorrelation between differing lag lengths of the time series. Plotting the autocorrelogram is a useful aid for determining the stationarity of a time series, and is also an important input into Box-Jenkins model identification. The theoretical autocorrelogram for different orders of AR, MA and ARMA models are outlined in section dealing with model identification. If a time series is stationary then its autocorrelogram should decay quite rapidly from its initial value of unity at zero lag. If the time series is nonstationary then the autocorrelogram will only die out gradually over time. Based on a graphical examination of Figure 1.1, the first difference of logs require more formal unit root testing to determine stationarity.

Figure 1.1: General Trend of Pakistan's Monthly Inflation: Period: 1992-93 through 2003-04

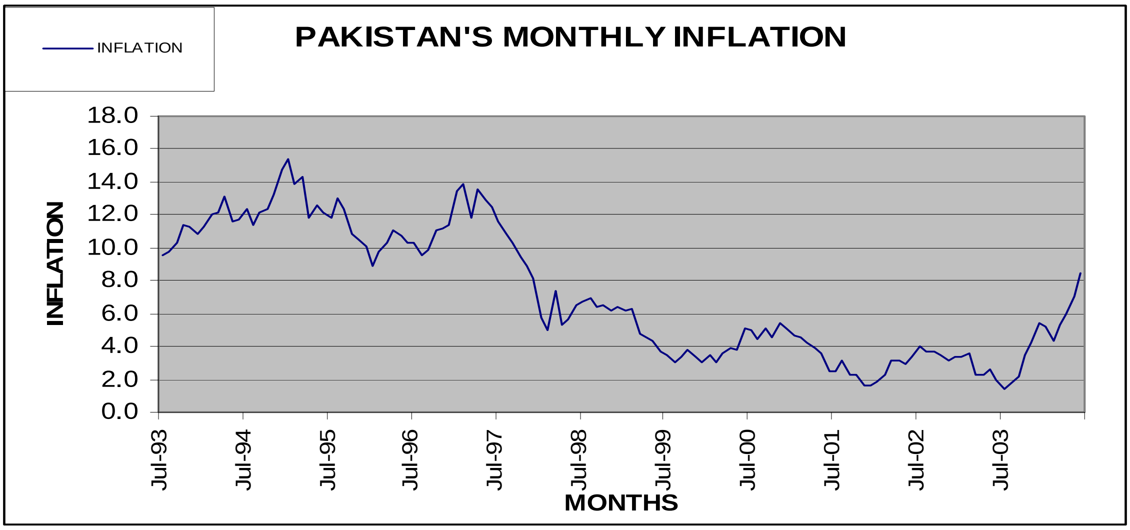


Figure 1.2: Period wise Break-up & 12 Month ahead Forecast of Pakistan's Monthly Inflation: Period: 1992-93 through 2003-04

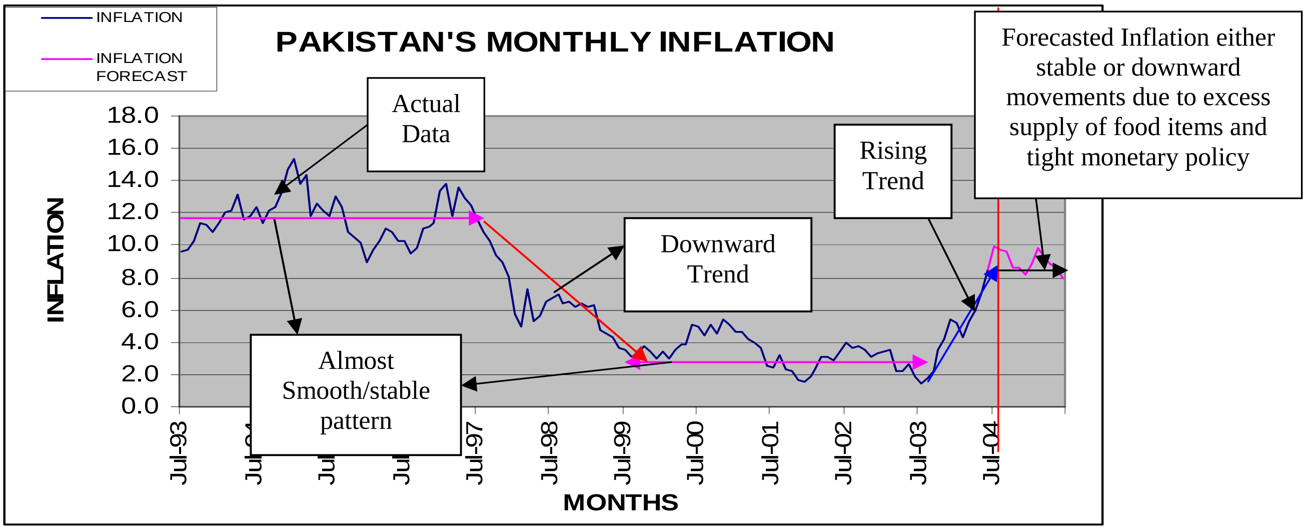


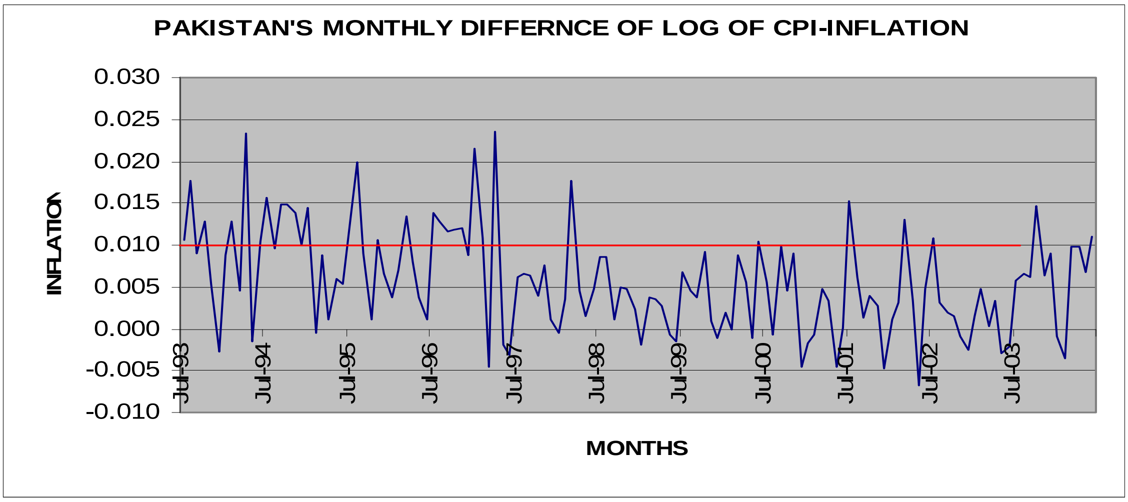
Table 2.1: Unit Root Test

ADF Test Statistic	-2.040813	1% Critical Value*	-3.4807
		5% Critical Value	-2.8833
		10% Critical Value	-2.5783
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Table 2.2: Unit Root Test (After Difference & Log Transformation)

ADF Test Statistic	-8.440674	1% Critical Value*	-3.4807
		5% Critical Value	-2.8833
		10% Critical Value	-2.5783
*MacKinnon critical values for rejection of hypothesis of a unit root.			

Figure 1.3: First Difference of Log of CPI



5.2 TESTING FOR STATIONARITY: THE UNIT ROOT TEST

The time series under consideration must be stationary before one can attempt to identify a suitable ARMA model. A large literature has developed in recent years on the issue of testing time series for stationarity and nonstationarity (See, for example, Harris (1995) and Banerjee *et al* (1993)). For AR or ARMA models to be stationary it is necessary that the modulus of the roots of the AR polynomial be greater than unity, and for the MA part to be invertible it is also necessary that the roots of the MA polynomial lie outside the unit circle.

To check the stationarity of the data, we plot the graph of the monthly consumer price inflation (CPI) as shown in the figure 1.1 & 1.2. It is evident that there are large swings in the data indicating that it may be non-stationary, so we apply Dickey Fuller (DF) unit root test to the data to check for stationarity. The DF test results are presented in table 2.1. At the level the test suggest that it is non-stationary as reflected from the tables and also evident from the auto correlation function (see Figure 1.4). In such circumstances Box, Jenkins recommends differencing the data so we see it at first difference.

At first difference the null hypothesis of unit root is rejected and we conclude that the data is stationary at first difference i.e. CPI data are integrated of order (1). In order to further smooth the fluctuations existing in the data we undergo another step of taking simple log of the price. Normally to minimize the severity of the data log variable is used. Our finding suggests that this variable is also non-stationary at level but stationary at first difference as indicated by the number appearing in the table 2.2.

5.3 MODEL IDENTIFICATION AND ESTIMATION

Having determined the correct order of differencing required to render the series stationary, the next step is to find an appropriate ARMA form to model the stationary series. There are number of alternative identification methods proposed in the literature. These include, *inter ali*a, the Corner method (Beguin *et a*l, 1980), the R and S Array method (Gray *et a*l, 1978), and canonical correlation methods (Tsay and Tiao, 1985). Objective measures of model suitability, the penalty function criteria see Gómez and Maravall (1998). These methods are usually based on the properties of the autocorrelation function and do not require estimation of a range of models, which can be computationally expensive. The traditional and most commonly used method utilizes the Box-Jenkins procedure, in which an iterative process of model identification, model estimation and model evaluation is followed. The Box-Jenkins procedure is a quasi-formal approach with model identification relying on subjective assessment of plots of autocorrelograms and partial autocorrelograms of the series.

The Box-Jenkins methodology essentially involves examining plots of the sample autocorrelogram and partial autocorrelogram and inferring from patterns observed in these functions the correct form of ARMA model to select. The Box-Jenkins methodology is not only about model identification but is, in fact, an iterative approach incorporating model estimation and diagnostic checking in addition to model identification. Theoretically speaking, Box-Jenkins model identification is no doubt a highly subjective exercise and depends entirely on the skill and experience of the researcher/forecaster.

Now empirically speaking, after making the data stationery we then estimate the simple model to decide about ARIMA term(s). The correlogram of residuals indicates that the model follows AR process. So we estimated the model with some AR terms at the second stage**,** since there was still serious correlation at various lags as reflected from the correlogram of residuals so we went for another step. We have estimated the model with different AR and MA terms keeping in view the properties of residuals like independence, homoskedacticity and normality. After estimating the model we again checked the correlogram of residuals (see figure 2.2 & 2.3). On the basis of this diagram, we decided that since this time there is no serious autocorrelation in the model and other residual properties are well satisfied, therefore, the model is seems fit for forecasting.

Keeping in mind the general rule of thumb for univariate ARIMA forecasting is to test, test and test at all stages of the ARIMA process, so by doing the same we have established various ARIMA models among which the three suitable models which were satisfying all the properties of residual. Further the parameters were significantly impacting the inflation.

5.4 MODEL DIAGNOSTICS

The fourth step will be the formal assessment of each of the time series models. This will involve a rigorous assessment of the diagnostic tests for each of the competing models. As different models may perform reasonably similarly, a number of alternative formulations may have to be retained at this stage to be further assessed at the forecasting stage. There are a number of diagnostic tools available for ensuring a satisfactory model is arrived at. Plotting the residuals of the estimated model is a useful diagnostic check. This should indicate any outliers that may affect parameter estimates and also point towards any possible autocorrelation or heteroscedacity problems. A second check of model suitability is to plot the autocorrelogram of the residuals. If the model is correctly specified the residuals should be 'white noise'. Therefore, a plot of the autocorrelogram should immediately die out from one lag on. Any significant autocorrelations may indicate that the model is misspecified.

Keeping in view the general properties of residuals as mentioned earlier, one has to empirically prove or disprove these prerequisite of model diagnostics, so by doing the same we have established various ARIMA models among which the three suitable models which were satisfying all the properties of residual and other diagnostic rules like R-squared, Adjusted R-squared, S.E. of regression, Durbin-Watson statistic, Skewness, Kurtosis and Jarque-Bera test which are presented in table 5.

5.5 FORECAST EVALUATION AND FORECAST ACCURACY CRITERIA

To assess the out-of-sample forecasting ability of the model it is advisable to retain some observations at the end of the sample period which are not used to estimate the model. One approach is to estimate the model recursively and forecast ahead a specific number of observations. For example, consider a time series with data from July, 1993 to June, 2004 and we wish to forecast twelve steps ahead July through June of 2004-05. These can be used to calculate statistics such as mean error (ME), mean absolute error (MAE), root mean squared error (RMSE) and Theil's U.

One indication that the model specification could be improved is if the ME for each of the five steps is either all positive or all negative. This would indicate that the model is either forecasting too low on average (if positive) or too high on average (if negative). If the ME is of the same magnitude as the MAE this would also indicate that the model is forecasting consistently either too low (if the ME is positive) or too high (if the ME is negative). The RMSE will always be at least as large as the MAE. They will only be equal if all errors are exactly the same. Theil's U statistic calculates the ratio of the RMSE of the chosen model to the RMSE of the 'naive' (i.e., assuming the value in the next period is the same as the value in this period - no change in the dependent variable) forecasting model. Thus, a value of one for the Theil statistic indicates that, on average, the RMSE of the chosen model is the same as the 'naive' model. A Theil statistic in excess of one would lead one to reconsider the model as the simple 'naive' model performs better, on average. A Theil statistic less than one does not lead to automatic acceptance of the model, but does indicate that, on average, it performs better than the 'naive' model. The advantage of the Theil statistic is that it is 'unit less' as it compares the RMSE of the chosen model to that of the 'naive' forecast model. The ME, MAE and RMSE all vary depending on the dimension (or scale of measurement) of the dependent variable. The Theil statistic also provides a quick comparison with the ‘no change’ model and, as such, is a measure for one-step ahead forecasts of the additional forecasting information the model provides beyond a random walk model. An additional test of the ARIMA model would be to compare its performance with competing models including alternative ARIMA specifications models.

Empirically taking, we have examined that Table 5 reports the various measures of forecasting errors, namely the root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) and Theil’s U and other selection criteria for different models. The first two forecast error statistics depend on the scale of the dependent variable. These are used as relative measures to compare forecasts for the same series across different models, the smaller the error, the better the forecasting ability of that model accordingly. The remaining two statistics are scale invariant. The Theil inequality coefficient always lies between zero and one, where zero indicates a perfect fit. To measure forecasting ability we have estimated within sample and out of sample forecasts. The estimated model is then used to obtain the future forecasts. We have forecasted within the sample and out of sample CPI inflation data. The purpose of forecasting within the sample is to test for the predictability power of the model. If the magnitude of the difference between the forecasted and actual values is low then the model has a good forecasting power. In this case our model has shown good results as evident from the Table 5. One can observe from the figure that the forecast series are much closer to the actual series. As the predicted value closely follow/capture both past and future inflation trend. So it can be concluded from the findings that the prediction power of the model is better and suitable for twelve periods ahead forecasting. Due to this objectivity in computation, we here proposed three models which are highly supported by ARIMA model selection criteria. The *best* model is proposed among the three estimated models on the basis of model diagnostic checking, forecast evaluation and forecast accuracy as presented in table 3 & 5.

5.6 THE BEST MODEL

The proposed model is given as:

$$\mathbf{Y_t = \alpha_0 + \Phi_1 Y_{t-1} + \alpha_2 Y_{t-3} + \alpha_3 Y_{t-8} + \alpha_4 Y_{t-12} + \beta_1 \varepsilon_{t-1} + \beta_2 \varepsilon_{t-10}} \text{--------------} \mathbf{(1)}$$

OR

$$\mathbf{Y_t = 0.006 - 0.46\, Y_{t-1} - 0.21\, Y_{t-3} - 0.18\, Y_{t-8} - 0.21\, Y_{t-12} + 0.58\, \varepsilon_{t-1} - 0.25\, \varepsilon_{t-10}} \text{------------} \mathbf{(1)}$$

The above model is selected on the basis of its overall forecasting performance and it meets the entire prerequisites which are well in line and support the model regarding its robustness, forecasting evaluation and its forecasting accuracy is concerned. The supporting statistics like R-squared, Adjusted R-squared, S.E. of regression, Durbin-Watson statistic, Akaike information criterion, Schwarz criterion, F-statistic, Skewness, Kurtosis, Jarque-Bera, Root Mean Squared Error, Mean Absolute Error, Mean Abs. Percent Error, Theil Inequality Coefficient, Bias Proportion, Variance Proportion and Covariance Proportion have outperformed as compared to other models like (2) & (3) which can be seen through tables 3, 4 & 5.

Having this positive behavior of the model, the model has also outperform as for as the forecasting power of the model is concerned. This predictive power of the model indicates that actual and predicted values have high level of close match.

5.7 POST FORECASTING ANALYSIS: CURRENT INFLATION TRENDS

Actual inflation averaged 9.26 percent during the first ten months July through April (see table 4) of the current fiscal year as against 3.9 percent in the same period last year. At 9.26 percent, inflation is at 8 year high in 2004-05. Food inflation recorded at 12.8 percent compared with 4.9 percent for the same period last year. Non-food inflation rose to 6.9 percent as against 3.3 percent in the same period last year. Core inflation, arrived at by excluding food and energy inflation, also indicated a rising trend for the period under review, increasing from 3.3 percent to 7.4 percent. The sharp upturn in inflationary trend is caused by demand pressures on the one hand and supply shocks on the other. Three years of strong economic growth in succession have given rise to the income levels of various segments of society. The rising levels of income have strengthened domestic demand which contributed to the rise in inflationary pressure. Supply side pressures emanated from a combination of factors. Successive increases in the support price of wheat in the last two years, shortage of wheat owing to less than the targeted production (in 2003-04); and the mismanagement of wheat operation, resulted in sharp increases in the prices of wheat and wheat-flour. The price of other food items registered sharp increases owing to ‘sympathy effect’ on the one hand and demand pressure on the other. The pass-through impact on CPI-based inflation of an increase in wheat support price is both significant as well as empirically well established. In addition, a surge in international oil prices coupled with an unprecedented rise in world prices of commodities have combined to spark inflationary pressure. House rent index also played an important role in building inflationary pressure this year. With second largest weight in the CPI (23.4%) after food (40.3%), the persistent rise in this index has contributed substantially to the increase in CPI – inflation. From a level of 3.8 percent last year, the index recorded an increase of 11.1 percent. This rise in inflation has not only impacted the overall economy but also most importantly its adverse and disproportionate effect on the poor and vulnerable segments of society. Further its deleterious effect on purchasing power of the fixed-income group is also quite obvious and crystal clear.

The Forecasted inflation averaged 9.29 percent during the first ten months July through April of the current fiscal year as compared to actual inflation which stood 9.26 percent in the same period. So the average forecast error between actual inflation and forecasted inflation is merely 0.03 percent (see table 4), which indicates that the model has the strong power of predictability.

The May through June forecasted inflation has showing either stable or downward trend which is quite in line with the government policies both at fiscal & administrative side and monetary side. Infact the government has responded in a multi-pronged manner to the rise in the price level but has not been successful so for. A strategy of regular monitoring of domestic stocks of key commodities and their prices was adopted, by which the government was able to respond in a timely manner to shortages by importing substantial quantities of wheat and other essential commodities including eleven kitchen items to augment supplies. To ease off the demand pressures generated by the rising level of economic activity, the State Bank of Pakistan (SBP) began to tighten monetary cycle. However, detailed analysis suggests that the increase was driven principally by POL and food product prices meant that SBP policy had a relatively small role in containing these supply-side pressures. In fact, the composition of the CPI inflation pressures suggests that anti-inflationary policies will need to focus more on administrative and fiscal measures. The easing of demand pressure through monetary policy and improving the supply situation of food items, either through raising their production or through imports, are likely to put downward pressure on general price level in coming months.

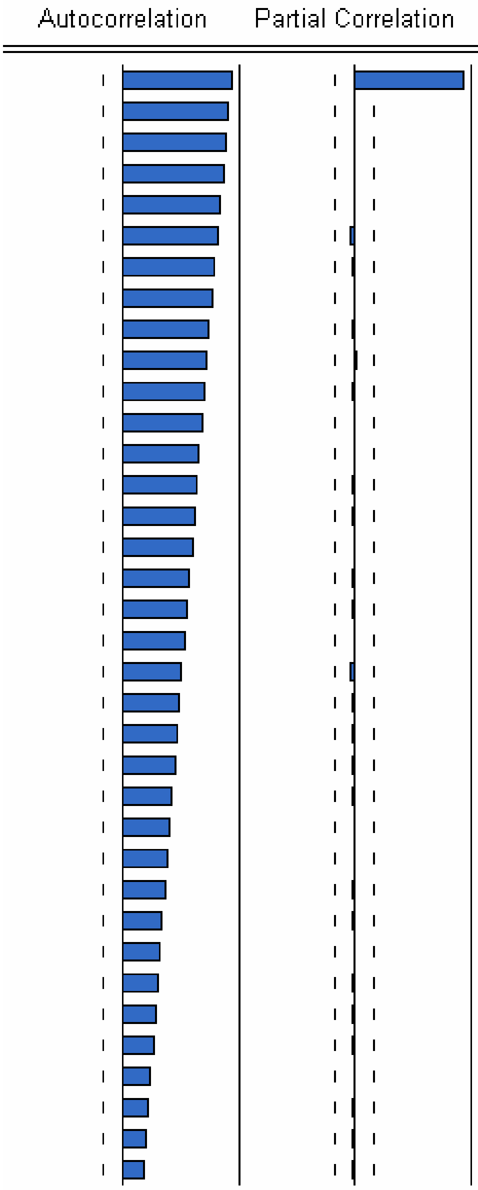
6. CONCLUDING REMARKS

This research work is an attempt to select the best and accurate model among various ARIMA estimated models which posses' high power of predictability (forecasting power). We have identified a framework for ARIMA modeling which includes the following steps: data collection and examination; determining the order of integration; model identification; diagnostic checking; model stability testing; and forecast performance evaluation. We have adopted the traditional Box-Jenkins approach of forecasting known as ARIMA modeling, in which a time series is expressed in terms of past values of itself (the autoregressive component) plus current and lagged values of a 'white noise' error term (the moving average component). The primary purpose behind this study was to find out which ARIMA model is more accurate and appropriate for forecasting purposes in the real world situation, keeping in view the cost of model building.

A general rule of thumb for univariate forecasting is to test, test and test at all stages of the ARIMA process. ARIMA models are theoretically justified and can be surprisingly robust with respect to alternative (multivariate) modeling approaches. Indeed, Stockton and Glassman (1987, pg. 117) upon finding similar results for the United States commented that "it seems somewhat distressing that a simple ARIMA model of inflation should turn in such a respectable forecast performance relative to the theoretically based specifications..

The study is based on Pakistan's monthly inflation data, which has used to estimate various possible ARIMA models. Among these estimated models, the best model for inflation forecast for the period 2004:07 to 2005:06 have been obtained. The comparative performance of these ARIMA models have checked and verified by using the statistics; AIC, RMSPE, MAE, MPB and MAPE. The comparison indicates that the best ARIMA model (1) performs much better than the rest of the estimated models. It has also observed that the plots of actual values of the variables and those of the predicted values based on accurate ARIMA model are closer than those of other ARIMA models.

Figure 1.4: Correlogram of Original CPI Series



Lag	AC	PAC	Q-Stat	Prob
1	0.974	0.974	128.06	0.000
2	0.949	0.006	250.53	0.000
3	0.924	-0.005	367.59	0.000
4	0.900	0.000	479.49	0.000
5	0.876	-0.005	586.39	0.000
6	0.851	-0.035	688.10	0.000
7	0.826	-0.021	784.61	0.000
8	0.801	-0.001	876.18	0.000
9	0.776	-0.016	962.88	0.000
10	0.754	0.020	1045.2	0.000
11	0.730	-0.014	1123.2	0.000
12	0.708	-0.006	1197.0	0.000
13	0.686	-0.001	1266.9	0.000
14	0.663	-0.019	1332.7	0.000
15	0.641	-0.015	1394.8	0.000
16	0.619	-0.004	1453.1	0.000
17	0.597	-0.011	1507.9	0.000
18	0.575	-0.008	1559.2	0.000
19	0.554	-0.004	1607.2	0.000
20	0.532	-0.030	1651.9	0.000
21	0.510	-0.019	1693.2	0.000
22	0.487	-0.023	1731.4	0.000
23	0.464	-0.017	1766.3	0.000
24	0.441	-0.017	1798.3	0.000
25	0.420	0.003	1827.4	0.000
26	0.399	0.004	1853.9	0.000
27	0.377	-0.022	1877.9	0.000
28	0.356	-0.022	1899.4	0.000
29	0.335	0.005	1918.6	0.000
30	0.315	-0.012	1935.8	0.000
31	0.294	-0.021	1950.9	0.000
32	0.273	-0.024	1964.1	0.000
33	0.252	-0.005	1975.5	0.000
34	0.232	-0.010	1985.2	0.000
35	0.212	-0.017	1993.4	0.000
36	0.192	-0.017	2000.1	0.000

Figure 2.1: Residual Correlogram

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.016	0.016	0.0349	
		2	0.006	0.006	0.0406	
		3	-0.053	-0.053	0.4233	
		4	0.014	0.016	0.4522	
		5	-0.022	-0.022	0.5191	
		6	0.061	0.059	1.0386	
		7	0.104	0.104	2.5545	0.110
		8	-0.019	-0.026	2.6049	0.272
		9	0.014	0.021	2.6338	0.452
		10	0.066	0.076	3.2685	0.514
		11	0.002	-0.004	3.2693	0.659
		12	-0.062	-0.061	3.8392	0.698
		13	0.077	0.075	4.7276	0.693
		14	0.086	0.077	5.8311	0.666
		15	-0.070	-0.079	6.5706	0.682
		16	0.084	0.087	7.6562	0.662
		17	0.095	0.091	9.0524	0.617
		18	0.034	0.029	9.2295	0.683
		19	-0.048	-0.037	9.5913	0.727
		20	0.017	-0.005	9.6374	0.788
		21	-0.034	-0.032	9.8226	0.831
		22	-0.020	-0.010	9.8897	0.872
		23	0.073	0.037	10.746	0.869
		24	0.141	0.111	14.022	0.728
		25	0.118	0.141	16.316	0.636
		26	-0.057	-0.064	16.867	0.662
		27	0.151	0.142	20.724	0.476
		28	-0.052	-0.017	21.176	0.510
		29	-0.035	-0.042	21.382	0.558
		30	-0.036	-0.072	21.609	0.603
		31	0.022	-0.026	21.691	0.654
		32	-0.012	-0.015	21.717	0.704
		33	-0.026	-0.060	21.838	0.746
		34	-0.008	-0.067	21.849	0.788
		35	-0.068	-0.052	22.704	0.790
		36	0.119	0.163	25.301	0.710

Figure 2.2: Residual Square of Correlogram

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.042	0.042	0.2358	
		2	0.186	0.185	4.9544	
		3	0.109	0.099	6.5933	
		4	0.044	0.005	6.8648	
		5	-0.042	-0.084	7.1063	
		6	-0.017	-0.037	7.1474	
		7	0.066	0.089	7.7645	0.005
		8	0.004	0.027	7.7671	0.021
		9	0.017	-0.003	7.8072	0.050
		10	0.070	0.047	8.5187	0.074
		11	0.072	0.060	9.2672	0.099
		12	0.050	0.035	9.6373	0.141
		13	-0.107	-0.151	11.331	0.125
		14	-0.013	-0.052	11.356	0.182
		15	0.022	0.074	11.428	0.248
		16	-0.094	-0.045	12.776	0.236
		17	0.060	0.063	13.325	0.273
		18	-0.033	-0.047	13.497	0.334
		19	-0.058	-0.092	14.023	0.372
		20	-0.010	0.017	14.040	0.447
		21	-0.041	-0.025	14.313	0.502
		22	-0.064	-0.064	14.978	0.526
		23	-0.055	-0.021	15.470	0.562
		24	-0.047	-0.015	15.838	0.604
		25	-0.098	-0.058	17.415	0.562
		26	0.016	0.038	17.458	0.623
		27	-0.049	-0.037	17.858	0.658
		28	-0.015	-0.001	17.896	0.712
		29	0.033	0.048	18.087	0.753
		30	-0.110	-0.099	20.171	0.687
		31	-0.030	-0.027	20.324	0.730
		32	0.044	0.076	20.659	0.759
		33	0.134	0.207	23.857	0.638
		34	-0.042	-0.052	24.180	0.672
		35	0.168	0.085	29.316	0.449
		36	0.017	-0.016	29.368	0.498

Figure 3.1: Normality Test

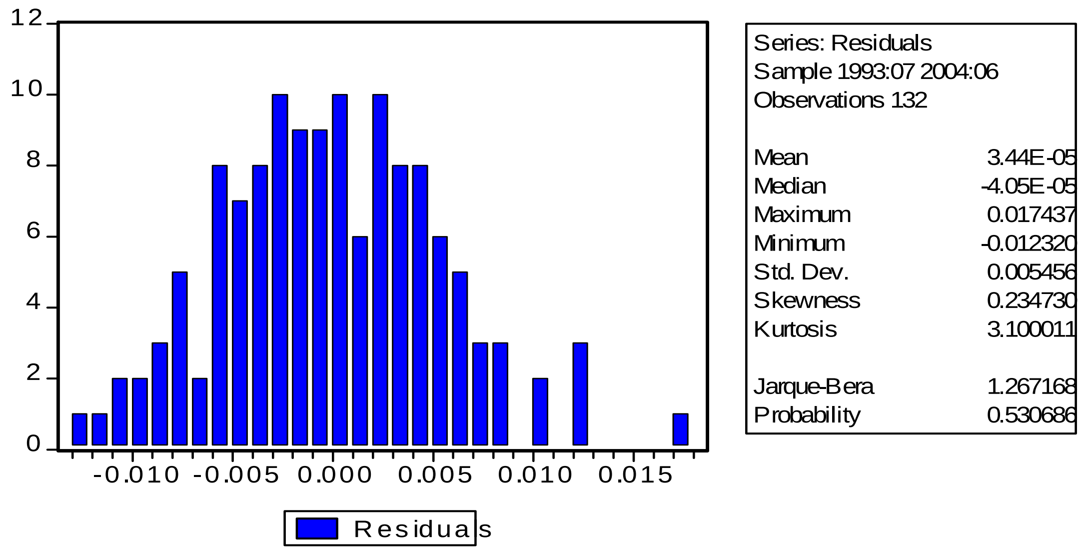


Figure 3.2: Residual Test

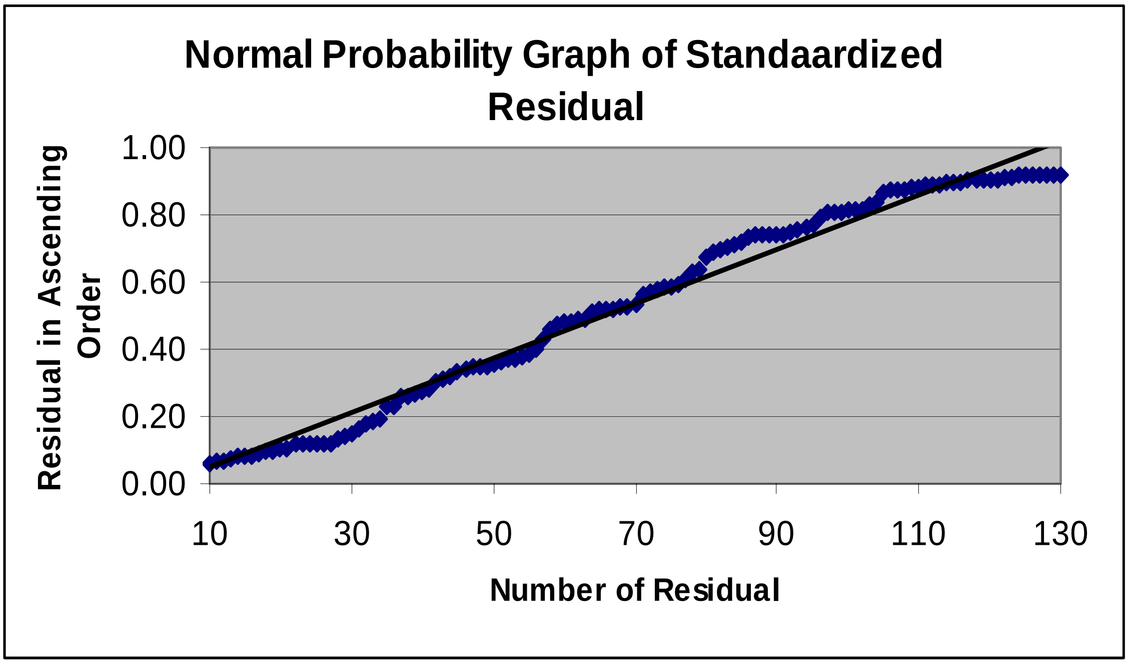


Figure 4.1: Residual Actual and Fitted

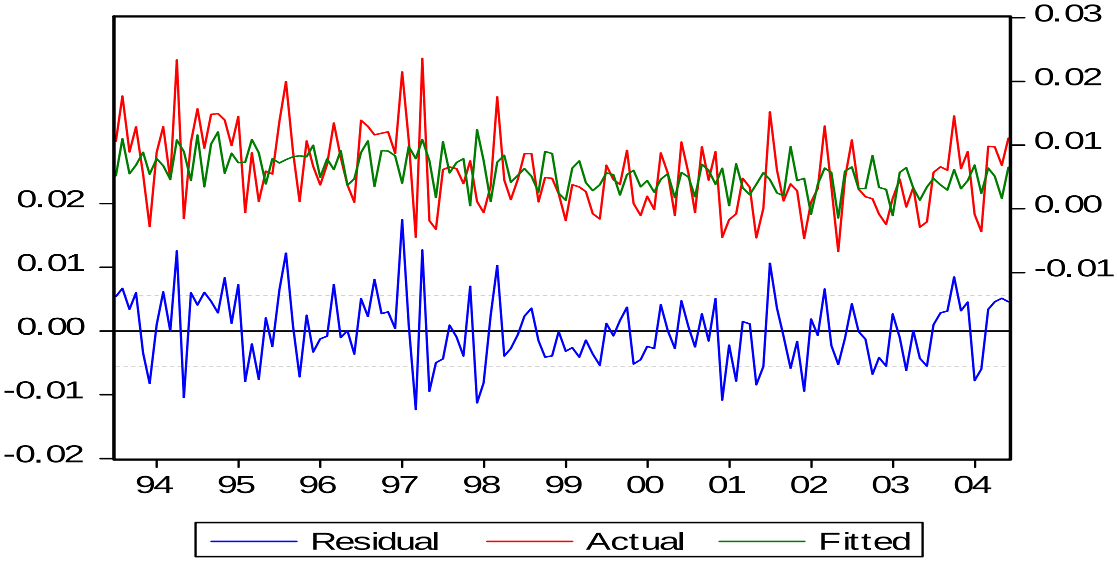


Table 3: Best Model Specification

SHORT TERM 12-MONTHS PAKISTAN'S INFLATION FORECAST

[$Y_t = 0.006 - 0.46\ Ұ_{t-1} - 0.21\ Y_{t-3} - 0.18\ Y_{t-8} - 0.21\ Y_{t-12} + 0.58\ \varepsilon_{t-1} - 0.25\ \varepsilon_{t-10}$]

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005520	0.001120	4.929571	0.0000
AR(8)	0.177667	0.083959	2.116107	0.0363
AR(12)	0.205407	0.090795	2.262321	0.0254
AR(3)	0.214867	0.090858	2.364875	0.0196
SAR(1)	-0.464943	0.201928	-2.302522	0.0230
MA(1)	0.584657	0.176589	3.310841	0.0012
MA(10)	-0.250625	0.081046	-3.092377	0.0024
R-squared	0.212518	Mean dependent var		0.005742
Adjusted R-squared	0.174719	S.D. dependent var		0.006149
S.E. of regression	0.005586	Akaike info criterion		-7.485593
Sum of squared residual	0.003900	Schwarz criterion		-7.332717
Log likelihood	501.0492	F-statistic		5.622295
Durbin-Watson stat	1.955016	Prob(F-statistic)		0.000034

Figure 4: Actual & 12 Month Centered Moving Average along with 12 Month ahead Forecast: Period: 2004-05 (July to June)

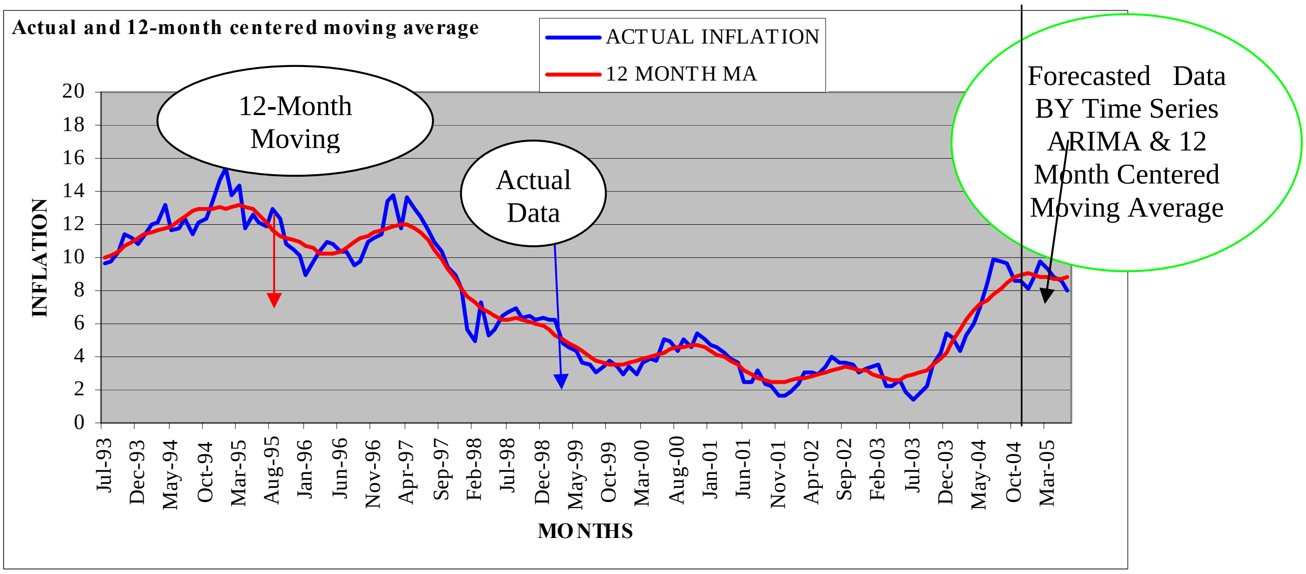


TABLE 4: SHORT TERM 12-MONTHS INFLATION FORECAST
$[Y_t = 0.006 - 0.46\ \text{¥}_{t-1} - 0.21\ Y_{t-3} - 0.18\ Y_{t-8} - 0.21\ Y_{t-12} + 0.58\ \varepsilon_{t-1} - 0.25\ \varepsilon_{t-10}]$

PERIOD	FORECASTED INFLATION	ACTUAL DATA	FORECAST ERROR
4-Jul	9.9	9.3	-0.6
4-Aug	9.7	9.2	-0.5
4-Sep	9.6	9	-0.6
4-Oct	8.6	8.7	0.1
4-Nov	8.6	9.3	0.7
4-Dec	8.2	7.4	-0.8
5-Jan	8.8	8.5	-0.3
5-Feb	9.8	9.9	0.2
5-Mar	9.3	10.2	0.9
5-Apr	10.4	11.1	0.7
5-May	9.6	N.A	N.A
5-Jun	9.1	N.A	N.A

Table 5: Comparison of Monthly CPI Inflation Forecast by ARIMA Models-Selection criteria and Forecast Evaluation (M-SC&FA)

ARIMA / M-SC&FA	SAR(1),AR(3), AR(8), R(12), MA(1), MA(10)	AR(1), MA(1)	SAR(1),AR(8), AR(12),MA(1), MA(10)
	(1)	**(2)**	**(4)**
R-squared	**0.2125**	0.1647	0.1776
Adjusted R-squared	**0.1747**	0.1518	0.1449
S.E. of regression	**0.0056**	0.0057	0.0057
Durbin-Watson stat	**1.9550**	1.9326	2.0002
Akaike info criterion	**-7.4856**	-7.4873	-7.4573
Schwarz criterion	**-7.3327**	-7.4218	-7.3263
F-statistic	**5.6223**	12.7199	5.4408
Skewness	**0.2347**	0.3439	0.3998
Kurtosis	**3.1000**	3.3538	3.3859
Jarque-Bera	**1.2672**	3.2899	4.3357
Probability	**0.5307**	0.1930	0.1144
Root Mean Squared Error	**7.8288**	10.4805	8.2048
Mean Absolute Error	**6.6259**	9.5184	6.9758
Mean Abs. Percent Error	**7.6114**	10.1087	8.0304
Theil Inequality Coefficient	**0.0450**	0.0615	0.0472
Bias Proportion	**0.6887**	0.8248	0.7025
Variance Proportion	**0.0075**	0.1473	0.0078
Covariance Proportion	**0.3037**	0.0279	0.2897

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