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Inflation Forecasting under Different Macroeconomic Conditions: A Case Study of Pakistan

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Abstract

Inflation forecasting is of primary importance not only for the conduct of monetary policy, but also for individuals to make choices. Forecasting inflation provides the precise image of how the economy is expected to accomplish in the future. For forecasting inflation, personal consumption expenditure is used to measure inflation because of its superiority of less sensitivity of price shock and its revision in subsequent years. For inflation forecasting, naive model, ARIMA model, Philips curve model, and Philips curve threshold autoregressive model are applied under different macroeconomic conditions with real-time, revised and final data from 1974 to 2016. The result shows that the naive model is superior to other models because RMSE and MAE of naive model are smaller than other models by using real-time, revised and final data for one year-ahead out-of-sample inflation forecasting. However, for two years ahead out of the sample inflation forecast, the real-time data RMSE shows that the naive model outperforms the other models, whereas the MAE shows that Philips curve threshold autoregressive model is superior than other models. For revised and final data for two years ahead out-of-sample inflation forecasting both forecasting accuracy measures show the naive model performance is the best.

.***Keywords:*** inflation forecasting, macroeconomic conditions, naive model, ARIMA model, Philips Curve model.

JEL Classification Codes: C53

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1. Introduction

Inflation forecast always remain a great interest for the central banks for the conduct of monetary policy. Reliable inflation forecast is not only helpful for the central bank to achieve their aims but also for the agents in decision making about price and wage contracts. If unexpected high inflation prevails, it will be particularly costly for families that depend on pensions and bonds for long time period. If inflation level is higher than the expected inflation, it will decrease household real purchasing power, because usually nominal income earned form such assets is fix. Accordingly, the standard of living of senior retired citizen is severely affected as they age. An unanticipated increase in inflation similarly have the tendency to decrease the labor wage and their real buying. Firms and families have to spend their energies and time to reduce the currency holding and businesses to frequent adjustment in price level. Further, the cost of capital is likely to be increased by high inflation after tax payment, in this way, the business investment will decrease. Therefore, such adverse outcome is a consequence of capital depreciation (Yellen, 2015).

The time series properties of inflation measures, however, have substantial revision over time as shown by Cogley and Sargent (2002, 2005). Like the other macroeconomic variables, the measure of inflation is also real-time data, and subject to revise in subsequent years. Usually this revision process completes in third year, when final estimates of a particular variable are available. So for each variable, three types of estimates, real time, revised and final estimates are available. The activity of revision analysis provides an opportunity for the users and creator of the data to analyze that to which extent and direction revisions take place.

It is important to choose the suitable model for inflation forecasting. (Kanyama & Thobejane, 2013) stated that it is an essential job for the researchers to examine which methods are suitable and ample to carry out a reliable prediction of inflation that policymakers can utilize to forecast inflation for effective allocation of resources. Different researchers have used different models to forecast inflation. Hafer and Hein (1990) have assessed the relative predicting evaluation of interest rate based models and univariate model in predicting inflation. They claimed that the univariate model performs better than the other models. On the other hand, Stock and Watson (1999) said that out-of-sample inflation forecasting from traditional Philips curve remained better than other models.

Philips curve has been utilized as an essential tool around the globe for the guidance of the monetary policy to control price level. Nevertheless, many contemporary studies show that in past twenty-year inflation forecast based on the Philips curve, underperform the integrated moving average (1, 1) model, naive model or an unobserved stochastic volatility model. Thus the question arises that either in policy discussions, the Philips curve has to carry on a noteworthy place. Atkenson and Ohanain (2001) wrote the first paper that casts uncertainty about the effectiveness of Philip's curve. Their results showed that the naive model performs better than the Philip's curve model for inflation forecasting. Since then, in many papers, the relative forecasting performance has been explored, particularly by Stock and Watson (2007, 2008). Naive model performs better for 1 year ahead forecasting whereas Philips curve perform better for 2 years ahead inflation forecasting. Therefore, from the above studies, a proper opinion concerning the worth of inflation forecast from Phillips curve models is unclear because sometimes the Philips curve perform better than the naive model and sometimes underperform the naive model.

Fuhrer and Olivei (2010) also studied Stock and Watson's suggestion and found that the naive model underperforms a threshold model of Philips curve (PC-TAR). Rumler andValderrama (2010), compared the forecasting performance New Keynesian Phillips Curve (NKPC) with traditional Philips curve, AR, naive, VAR, Bayesian VAR model over short and long term. They found that NKPC better forecasts in short term quarter ahead inflation forecasting whereas naive and traditional Philips Curve better forecast inflation over the long period of one and two years ahead inflation forecasting. In most of the studies, researchers have used monthly and quarterly data.

Hafer and Hein (1990), Stock and Watson (1999), Fisher et al. (2002), Bokil and Schimmelpfennig (2005), Khan and Schimmelpfennig (2006), Haider and Hanif (2009), Sultana et al. (2013) used monthly data. On the other hand, Alles and Horton (1999), Atkenson and Ohanain (2001), Önder (2004) Stock and Watson (2007, 2008), Fuhrer and Olivei (2010), Zardi (2017) used quarterly data.

As in the above studies, we came to know that different models have been utilized to forecast inflation over different periods in other countries. Whereas in the case of Pakistan, inflation is also forecasted by different models but no one has used these macroeconomics conditions regarding data. The objective of this research is to compare the forecast evaluation of the naive model, ARIMA model, Philips curve and Philips curve (TAR) model under different macro-economic conditions and select the most suitable model which provides good prediction under different macro-economic conditions concerning data (real-time, revised and final data).

We have also analyzed the differences between revised and real-time data, final and real-time data as well as final and revised data to perceive the direction of revisions take place.

2. Literature Review

Swanson (1996) stated that historical data is used by the macroeconomists, in order to test the models, analyze economic policy, economic events and forecasting. However, some studies have used historical unrevised data which is accessible to economic agents rather revised and final data that should be used. In other studies, in order to test the validity of results, published findings should be verified and robustness of such findings should be assessed using different datasets as revised and final data. Due to these reasons, data set was created that could give complete picture of macroeconomic data accessible to forecaster, academic researcher, and policy makers in past.

That research was focusing on two major aspects of data set. One potential reason of revision can be due to the fact that statistical agencies update initial projected estimates of measures as real-time GDP when they encounter with additional source of information other than the initially calculated aggregates. These revisions are based on information. Secondly, some other revisions result in change in structure of accounting system for economic data for example, changes in methods for aggregate calculation (such as chain or fixed weighting system) and alteration in base years (such as 1992 or 1997) that are used to calculate real variables. In addition, definition of concepts that are intended to measure also changes with time, which can lead to structural data revision (Croushore & Stark, 2003).

Rees (1970) stated that Philips curve has been an important tool from the past decade because it provides choices to the policy makers between inflation and unemployment. The Philips curve provides different trade-offs, then weights are assigned to both evils of inflation and unemployment by the policy makers. Alles and Horton (1999) used error correction model, interest rate based models, time series univariate model and survey method to evaluate the relative predicting power of these models and found that univariate model outperforms the other models. Fisher et al. (2002) compared the Naive model and general Philips curve model for one and two years inflation forecast horizon. They have used rolling regression and concluded that Philips curve model better forecasts inflation for 2 year time period and naive model better forecasts inflation for the period of time of one year.

Afzal et al. (2002) explored that a comparison is made between regressions based approaches and ARIMA models in Pakistan. They found that estimates obtained by using ARIMA model are closer to the actual values of the variable. Önder (2004) compared naive model, ARIMA model, and Phillips curve model, Philips curve constructed on macroeconomic indicators, VAR model and Vector Error Correction Model for inflation forecasting. It was concluded that Philips curve model better forecasts inflation relative to other models.

Orphanides and Van Norden (2005) used real time data and found that inflation forecast based on Philips curve performed better than autoregressive model before 1983, later on, ARIMA model better performed than Philips curve model from 1984-2002. Bokil and Schimmelpfennig (2005), used different methods to predict inflation that are the leading indicator model (LIM), ARIMA model, and VAR model. The preferred strategy is a leading model of indices in which broad money growth and credit growth in the private sector assist with inflation forecasting. In anticipating the inflation in Pakistan, Bokhari and Feridun (2006) used a number of methods, ARIMA and VAR models are used to evaluate the four distinct indices, SPI, CPI, WPI and GDP deflator to forecast inflation. The ARIMA (2, 1, 2) was found to perform better than the VAR models.

Khan and Schimmelpfennig (2006) examined which factors help inflation forecasting. They used monthly data from January 1998 to June 2005 to regress the inflation on monetary variables. Main indicators for inflation forecasting were money growth and private sector credit growth. According to Stock and Watson (2007), the Philips curve has a tendency to forecast well for a period less than a year. To forecast inflation in US, (Ang et al., 2007) examined the four different methods. That are, term structure model: which includes Arbitrage free, linear and nonlinear specifications, time series Autoregressive integrated Moving Average (ARIMA) model, Survey based method and regression based on Philips curve. They concluded that other methods do not perform well than survey based method.

Haider and Hanif (2009) used the artificial neural network (ANN). They have compared the inflation forecasting performance of univariate forecasting models e.g. ARIMA and AR (1) with ANN model. They concluded that ANN model better forecasts inflation than the univariate model. Fuhrer and Olivei (2010) also inspected the Stock and Watson evidence found that a threshold model of the Phillips curve better performs at naive model.

Sultana et al. (2013) said that in macroeconomics, forecasting time series is an important matter. They forecasted the CPI by using ARIMA and decomposition method. They used monthly data and compared forecast result by sum square of errors and mean absolute deviation and finds that ARIMA model better forecasts inflation. Zardi (2017) compared the forecasting performance of different models in short term by using quarterly data. They compared random walk benchmark model with Bayesian Vector Auto Regressive (BVAR), Factor Augmented Vector Auto Regressive (FAVAR), SRIMA and Time varying parameter model (TVAR) for inflation forecasting. Their results indicate that up to two quarter ahead other models better forecast than random walk model. However, at four quarters ahead random walk model better forecasts inflation than other models.

3. Data and Methodology

For empirical evaluation of different forecast models under diverse macroeconomic conditions with real time, revised and final sample period 1974 to 2016 is used. The reason for using this time is the non-availability of final data. Because the real time data available for a particular year is provisional, subject to revised next year and final data is available in third year. The data of inflation and output is taken from the Economic Survey of Pakistan. Hanif and Malik (2015) highlighted that for inflation forecast, the basic question ascends is the choice of the measure of inflation, because the general price level can be accessed by Whole Sale price index (WPI), Sensitive Price Index (SPI), Consumer Price index (CPI), GDP deflator and also Personal Consumption Expenditures (PCE) .

Each measure of inflation has some merits and demerits. SPI is the most frequent measure of price index but some basic necessity goods are included from seventeen cities. In WPI, the services sector is not included. Similarly, if GDP deflator is also a measure of price index but with the limitation of low frequency. CPI is available at relatively high frequency and it also assesses inflationary trends, impact on households and most cautiously denotes the cost of living. In our analysis, we will follow Dotsey et al. (2018) and use Personal Consumption Expenditures (PCE) for inflation forecast because of two reasons. Firstly, when commodity price shocks occur, it is less influenced than CPI. Secondly, CPI is the unrevised measure and on the other side, PCE inflation is revised and considered as more appropriate measure. Therefore, we have forecasted inflation by using Household Consumption Expenditures.

The variable output gap i.e. difference between the actual and potential GDP, is not directly observed. For the measurement of output gap, we used Hodrick and Prescott filter and find smoothed GDP as proxy of potential GDP. Thus we use output gap as a measure of unemployment, as Jahan and Mahmud (2013) observed that the theory of output gap is closely linked to unemployment gap.

Different models are available in the literature for the analysis of forecast evaluation of inflation. For this study, we will apply Naive model, ARIMA model, Philips curve Auto-regressive model, and Philips curve Threshold Auto-regressive model.

3.1. Naive model

The naive model makes a prediction about inflation and state that inflation for future year is anticipated to be equal to the inflation of previous year. We have estimated RMSE of the model under different macroeconomic conditions (real, revised and final data) by using sample period from 2014 to 2016. Equations are given below from 3.1 to 3.3.

$$E\left(inf_{t+1}^{rl} - inf_t^{rl}\right) = 0 \tag{3.1}$$

where
inf_{t+1}^{rl} = real-time inflation in next year
inf_t^{rl} = real inflation in previous year
$E\left(inf_{t+1}^{rl} - inf_t^{rl}\right)$ = real inflation in next year will be same that is in previous year.

Real inflation is subject to revisions, when real inflation is revised after one year. Then we have to estimate the RMSE of revised inflation. Below Equation 3.2 is related to the calculation of RMSE of revised inflation.

$$E\ (inf_{t+1}^{re} - inf_t^{re}) = 0 \tag{3.2}$$

where
inf_{t+1}^{re}= revised inflation in next year
inf_t^{re}= revised inflation in previous year
$E\ (inf_{t+1}^{re} - inf_t^{re})$ = revised inflation in next year will be same as it was in previous year.

Real inflation is subject to revisions, when real inflation is revised after second year. Then we have to estimate the RMSE of final inflation. Below mentioned equation 3.3 is related to the calculation of RMSE of final inflation.

$$E\left(inf_{t+1}^{fl} - inf_t^{fl}\right) = 0 \tag{3.3}$$

where
inf_{t+1}^{fl} = final inflation in next year
inf_t^{fl} = final inflation in previous year
$E\left(inf_{t+1}^{fl} - inf_t^{fl}\right)$ = final inflation in next year will be same at it was in previous year.

Fisher et al. 2002 stated that initial point for the explanation of naive model is martingale hypothesis, which stated that the sequence of expected value of inflation for the inflation over next 12 months is equal to the inflation over the previous 12 months.

3.2. ARIMA Model

Following Stock and Watson (2007), in this study we used the rolling ARIMA model under different macroeconomic conditions with (real-time, revised and final data) by using sample period from 1975 to 2014. .Later on, we roll forward our regression from 1975 to 2015 to forecast inflation for 2016 is given as below equations (3.4) to (3.6). We have estimated equation (3.4) for the estimation of real-time data. When real-time inflation is revised after one year, then we have estimated the revised inflation equation (3.5). After that when real-time inflation is revised after two years, then we have estimated the final inflation equation (3.6).

$$inf_t^{rl} = \varepsilon_{t-1} \tag{3.4}$$

where, inf_t^{rl} real inflation in current time. Our ARIMA is MA which shows that real inflation depends on shocks.

$$inf_t^{re} = inf_{t-2}^{re} + \varepsilon_{t-1} \tag{3.5}$$

where, inf_t^{re} is revised inflation in current time , inf_{t-2}^{re} is revised inflation at second lag, ε_{t-1} is revised inflation depends on the first lag of error term.

It means that revised inflation depends on its second lag as well as at shocks. Therefore, our ARIMA model is (2,1, 1).

$$inf_t^{fl} = inf_{t-1}^{fl} + \varepsilon_{t-1} \tag{3.6}$$

where, inf_t^{fl} = final inflation in current time , inf_{t-1}^{fl} =final inflation at first lag, ε_{t-1} = final inflation depend on the first lag of error term.

3.3. Philips Curve Auto-regressive Model (PCARM)

To explore the usefulness of the unconditional Philips curve model for forecasting of inflation, simple autoregressive Philip curve model was used in this research. Firstly, we have estimated the model for 1 period ahead out-of-sample inflation forecasting under different macroeconomic conditions (real-time, revised and final data) by using sample period from 1975 to 2014 and forecasted inflation for 2015. Later on, we roll forward our regression from 1975 to 2015 to forecast inflation for 2016 is given below in equation 3.7 to 3.9. We have estimated equation 3.7 for the estimation of real-time data. However, when real-time inflation is revised after one year then we have estimated the revised inflation equation 3.8. After that, when real-time inflation is revised after two years, then we have estimated the final inflation equation 3.9.

$$inf_t^{rl} = inf_{t-1}^{rl} \quad + og_t^{rl} + \varepsilon_t \tag{3.7}$$

where

inf_t^{rl} =real inflation in current time
inf_{t-1}^{rl} =real inflation at first lag
og_t^{rl} = real output gap at current time period.

$$inf_t^{re} = inf_{t-1}^{re} \quad + og_t^{re} + \varepsilon_t \tag{3.8}$$

where
inf_t^{re} = revised inflation in current time
inf_{t-1}^{re} = revised inflation at first lag
og_t^{re}= revised output gap at current time period.

$$inf_t^{fl} = inf_{t-1}^{fl} \quad + og_t^{fl} + \varepsilon_t \tag{3.9}$$

where
inf_t^{fl}= final inflation in current time
inf_{t-1}^{fl} = final inflation at first lag
og_t^{fl} = final output gap at current time period.

3.4. Philips Curve Threshold Auto-regressive Model (PCTARM)

We have to estimate the Philips Curve model for 2 period ahead inflation forecasting. Firstly, we have estimated the model for 1 period ahead out-of-sample inflation forecasting under different macroeconomic conditions (real-time, revised and final data) by using sample period from 1975 to 2014 and forecasted inflation for 2015. Afterwards, we roll forward our regression from 1975 to 2015 to forecast inflation for 2016. Further the difference between PC model and PC-TAR is an addition to the Phillips curve is the threshold term, with an effect of the threshold on the output gap. An absolute value of the output gap is threshold variable is given below equations 3.10 to 3.12. We have estimated equation 3.10 for the estimation of real time data however, the real-time data is subject to revisions. When real-time inflation is revised after one year, then we have estimated the revised inflation equation 3.11. After that, when real-time inflation is revised after two years, then we have estimated the final inflation equation 3.12

$$inf_t^{rl} = inf_{t-1}^{rl} + 1(|og_t^{rl}| > og_*^{rl})og^{rl} + 1(|og_t^{rl}| \leq og_*^{rl})og^{rl} + \varepsilon_t \tag{3.10}$$

where

inf_t^{rl}= real inflation in current time,

inf_{t-1}^{rl} = real inflation in previous year

$|og_t^{rl}|$ =absolute value of real output gap

og_*^{rl} = threshold level of real-time output gap,

$$inf_t^{re} = inf_{t-1}^{re} + 1(|og_t^{re}| > og_*^{re})og^{re} + 1(|og_t^{re}| \leq og_*^{re})og^{re} + \varepsilon_t \quad (3.11)$$

where

inf_t^{re} =revised inflation in current time

inf_{t-1}^{re} =revised inflation in previous year

$|og_t^{re}|$ =absolute value of revised output gap

og_*^{re} =threshold level of revised output gap

$$inf_t^{fl} = inf_{t-1}^{fl} - 1(|og_t^{fl}| > og_*^{fl})og^{fl} + 1(|og_t^{fl}| \leq og_*^{fl})og^{fl} + \varepsilon_t \quad (3.12)$$

where

inf_t^{fl} = final inflation in current time

inf_{t-1}^{fl} =final inflation in previous year

$|og_t^{fl}|$ =absolute value of revised output gap

og_*^{fl} = threshold level of final output gap,

4. Results and Discussions

4.1. Descriptive Statistics of Differences between Real, Revised and Final GDP

In this section, we have presented descriptive analysis of differences between real, revised and final GDP from the time period of 1974 to 2016. We have also divided our sample into five subsamples. We have descriptively analyzed the dataset as a measure of variability as well as the measure of central tendency. In this study, standard deviation and stability ratio is used as measure of variability. As we are familiar that only Standard Deviation (SD) is not the best measure of volatility because according to this measure, samples with the highest volatility also have the highest value of mean that is why it is better to use Stability ratio as a measure of volatility. We have used mean as a measure of central tendency. Several macroeconomic variables are projected estimates known as real-time data. Then they are subject to revisions with passage of time when new data is published. The activity of revision provides the opportunity to analyze the extent and direction of revisions. After one year, the data is revised and known as revised data. When data is revised after second year is known as final data. The results of differences between real, revised and final GDP are given in Table 1.

Table 1: Differences between Real, Revised and Final GDP

Variables	Years	Mean	SD	SR
Revised – Real GDP	1974-2016	-3,098	32882.64	-10.61
	1974-1980	7421.69	21381.96	2.88
	1981-1990	3563.547	24089.97	6.76
	1991-2000	-6188.32	32285.81	-5.22
	2001-2010	-12903.3	51008.51	-3.95
	2011-2016	-6519.45	16167.94	-2.48
Final- Real Time GDP	1974-2016	427	38314.88	89.73
	1974-1980	13464.47	25462.17	1.89
	1981-1990	11455.02	28816.63	2.52
	1991-2000	2610.92	27789.46	10.64
	2001-2010	-14233.1	62984.65	-4.43
	2011-2016	-14665.7	8848.737	-0.60
Final- Revised GDP	1974-2016	3,525	27050.21	7.67
	1974-1980	6042.777	16628.62	2.75
	1981-1990	7891.475	18393.33	2.33
	1991-2000	8799.242	35358.26	4.02
	2001-2010	-1329.79	35751.31	-26.88
	2011-2016	-8146.25	14110.84	-1.73

The table 1 shows that over entire sample average value of difference between revised and real-time GDP is -3,098. This value has a negative sign which indicates that revised GDP is less than real GDP and real GDP was overstated, on average over full sample GDP is revised in negative direction. On the other hand, over the subsample on average difference between revised and real GDP is more than the full sample, which indicates that over sub samples' revised GDP is lesser than real GDP and real GDP was more overstated, on average over subsamples' GDP is largely revised in negative direction than full sample.

The difference between revised and real GDP indicates that over the subsamples of 1974-1980, 1981-1990 average values are 7421.69 and 3563.54 respectively. These values have positive signs which indicates that revised GDP is more than real GDP and real GDP was understated, on average over 70s and 80s GDP is revised in positive direction. On the other hand, the difference between revised and real GDP shows that over the subsamples of 1991-2000, 2001-2010, 2011-2016 average values are -6188.31, -12903.33 and -6519.452 respectively. These values have negative signs which indicates that revised GDP is less than real GDP and real GDP was overstated, on average over these sub-sample GDP is revised in negative direction.

The difference between revised and real GDP indicates that over the subsample of 2001 to 2010, have higher standard deviation. It means that this subsample has more volatility as compared to other subsamples whereas the subsample 2011 to 2016 has lowest SD which means that this subsample has less volatility. According to SR subsample of 1981 to 1990 has the highest value of SR, meaning that this subsample is more volatile, whereas, the subsample of 1991 to 2000 has the lowest value of SR which shows the lowest volatility as compared to other subsamples.

The difference between final and real GDP indicates that over the subsamples of 1974-1980, 1981-1990, 1991-2000 average values are 13464.47, 11455.02 and 2610.92 respectively. These values have positive signs which indicates that final GDP is more than real GDP and real GDP was understated, on average, over 70s, 80s and 90s GDP is revised in positive direction. On the other hand, the difference between final and real GDP shows that over the subsamples of 2001-2010, 2011-2016 average values are -14233.12 and -14665.70 respectively. These values have negative signs which indicates that final GDP is less than real GDP and real GDP was overstated, on average over these sub-samples GDP is revised in negative direction.

The difference between final and real GDP indicates that over the subsample of 2001 to 2010 has higher standard deviation. It means that this subsample has more volatility as compared to other subsamples, whereas, the subsample of 2011 to 2016 has the lowest SD which means that this subsample has less volatility. According to SR, subsample of 1991 to 2000 has the highest value of SR, its means that this subsample is more volatile, whereas, the subsample of 2001 to 2010 has the lowest value of SR which shows the lowest volatility as compared to other subsamples.

The difference between final and revised GDP indicates that over the subsamples of 1974-1980, 1981-1990, 1991-2000 average values are 6042.777, 7891.475 and 8799.242 respectively. These values have positive signs which indicates that final GDP is more than revised GDP and revised GDP was understated, on average over 70s, 80s and 90s, GDP is revised in positive direction. On the other hand, the difference between final and revised GDP shows that over the subsamples of 2001-2010, 2011-2016 average values are -1329.79 and -8146.24 respectively. These values have negative signs which indicates that final GDP is less than revised GDP and revised GDP was overstated, on average over these sub-samples GDP is revised in negative direction.

The difference between final and revised GDP indicates that over the subsample of 2001 to 2010 has the highest value of standard deviation. It means that this subsample has more volatility as compared to other subsamples whereas the subsample of 2011 to 2016 has the lowest value of standard deviation. It means that this subsample has less volatility as compared to other subsamples.

4.2. Descriptive Statistics of Differences between Real, Revised and Final Inflation

In this section, we have presented descriptive analysis of differences between real, revised and final inflation from the time period of 1974 to 2016.

Table 2: Differences between Real, Revised and Final Inflation

Variables	Years	Mean	SD	SR
Revised - Real Inflation	1974-2016	-14001.79	452046.7	-0.03
	1974-1980	-13.92857	3751.575	0.00
	1981-1990	-5877.9	15631.02	-0.38
	1991-2000	195576.8	684762.5	0.29
	2001-2010	1600.7	379919.5	0.00
	2011-2016	-419162.5	571399	-0.73
Final- Real Inflation	1974-2016	-13058.84	472531.8	-0.03
	1974-1980	2094.42	3387.869	0.62
	1981-1990	-9003.85	17859.36	-0.50
	1991-2000	194343	670355	0.29
	2001-2010	58556.6	427652.1	0.14
	2011-2016	-502525	593977.6	-0.85
Final-Revised	1974-2016	942.9	115834.9	0.01
	1974-1980	2108.35	3951.029	0.53
	1981-1990	-3125.95	7498.416	-0.42
	1991-2000	-1233.8	21148.04	-17.14
	2001-2010	56955.9	197333.1	3.46
	2011-2016	-83362.5	163838.7	-0.51

The difference between revised and real inflation shows that over the subsamples of 1974-1980, 1981-1990, 2011-2016 average values are -13.92, -5877.9 and -419162.5 58556.60 respectively. These values have negative signs which indicates that revised inflation is less than real inflation and real inflation was overstated, on average over these subsample inflation is revised in negative direction. On the other hand, the difference between revised and real inflation indicates that over the subsamples of 1991-2000, 2001-2010, average values are 195576.8 and 1600.7 respectively. These values have positive signs which indicates that revised inflation is more than real inflation and real inflation was understated, on average over 90s and 20s inflation is revised in positive direction.

The difference between revised and real inflation indicates that over the subsample of 1991 to 2000 has higher standard deviation. It means that this subsample has more volatility as compared to other subsamples, whereas, the subsample 1974 to 1980 has the lowest SD which means that this subsample has less volatility. Therefore, according to SR subsample of 2011 to 2016 has the lowest value of SR, meaning that this subsample is least volatile, whereas, the subsample of 1991 to 2000 has the highest value of SR which shows the maximum volatility as compared to the other subsamples.

The difference between final and real inflation indicates that over the subsamples of 1974-1980, 1991-2000, 2001-2010 average values are 2094.42, 194343 and 58556.60 respectively. These values have positive signs which indicates that final inflation is more than real inflation and real inflation was understated, on average over 70s, 90s and 20s inflation is revised in positive direction. On the other hand, the difference between final and real inflation shows that over the subsamples of 1981-1990, 2011-2016 average values are -9003.85 and -502525 respectively. These values have negative signs which indicates that final inflation is less than real inflation and real inflation was overstated, on average over these sub-samples inflation is revised in negative direction.

The difference between final and real inflation indicates that over the subsample of 1991 to 2000 have higher standard deviation. It means that this subsample has more volatility as compared to other subsamples, whereas, the subsample 1974 to 1980 has the lowest SD which means that this subsample has less volatility. According to SR, subsample of 2011 to 2016 has the lowest value of SR, meaning that this subsample is least volatile whereas the subsample 1974 to 1980 has the highest value of SR which shows more volatility as compared to other subsamples.

The difference between final and revised inflation indicates that over the subsamples of 1974-1980, 2001-2010 average values are 2108.35 and 56955.90 respectively. These values have positive signs which indicates that final inflation is more than revised inflation and revised inflation was understated, on average over 70s and 20s inflation is revised in positive direction. On the other hand, the difference between final and revised inflation shows that over the subsamples of 1981-1990, 1991-2000, 2011-2016 average values are -3125.95, -1233.80 and -83362.50 respectively. These values have negative signs which indicates that final inflation is less than revised inflation and revised inflation was overstated, on average over these sub-samples inflation is revised in negative direction.

The difference between final and revised inflation indicates that over the subsample of 2001 to 2010 have higher standard deviation. It means that this subsample has more volatility as compared to other subsamples, whereas, the subsample of 1974 to 1980 has the lowest SD which means that this subsample has less volatility. According to SR, subsample 2001 to 2010 has the highest value of SR, meaning that this subsample is more volatile whereas the subsample of 1991 to 1990 has the lowest value of SR which shows the lowest volatility as compared to other subsamples.

4.3. Graph of Differences of Real, Revised and Final GDP

In this section, we have presented graphical analysis of differences between real, revised and final GDP from the time period of 1974 to 2016.The graph of differences between real, revised and final GDP is given below:

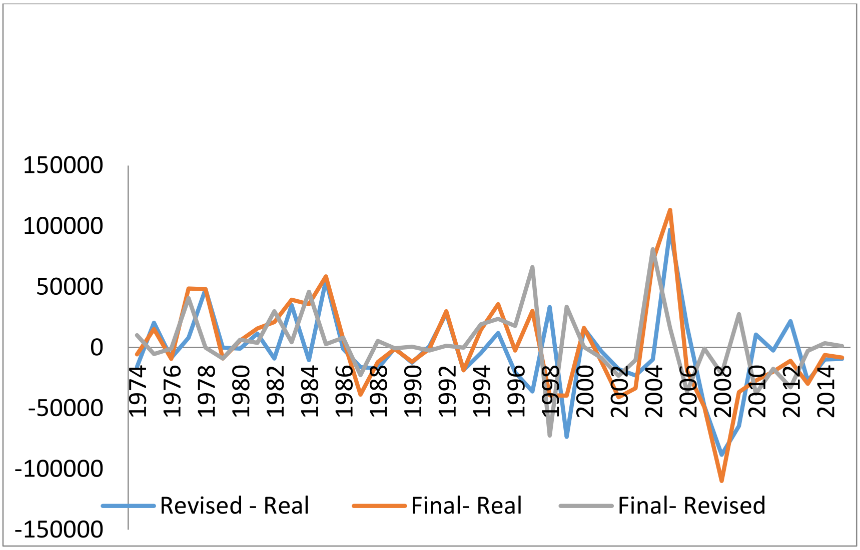

Figure 1: Differences of Real, Revised and Final GDP

The Figure 1 shows that over sub sample period from 1974-1980 and 1981-1990 mostly the difference between revised and real GDP is positive, which indicates that revised GDP is more than real GDP and real-time GDP was understated, on average over 70s and 80s GDP is revised in positive direction. On the other hand, over the subsamples from 1991-2000, 2001-2010, and 2011-2016 mostly the difference between revised and real GDP is negative, which indicates that revised GDP is less than real-time GDP and real-time GDP was overstated, on average over 90s, 2000s GDP is revised in negative direction.

It shows that over sub sample period from 1974-1980, 1981-1990, and 1991-2000 mostly the difference between final and real GDP is positive. It indicates that final GDP is more than real-time GDP and real-time GDP was understated, on average over 70s, 80s and 90s GDP is revised in positive direction. On the other hand, over the subsamples from 2001-2010, 2011-2016, mostly the difference between final and real GDP is negative. It indicates that final GDP is less than real GDP and real GDP was overstated, on average over 2000s GDP is revised in negative direction.

It shows that over subsample period from 1974-1980, 1981-1990, 1991-2000 mostly the difference between final and revised GDP is positive. It indicates that final GDP is more than revised GDP and revised GDP was understated, on average over 70s, 80s and 90s GDP is revised in positive direction. On the other hand, over the subsamples from 2001-2010, 2011-2016 the difference between final and revised GDP is negative. It indicate that final GDP is less than revised GDP and revised GDP was overstated, on average over 2000s GDP is revised in negative direction.

In 2005, the difference between revised and real GDP, final and real GDP, final and revised GDP is maximum as compared to other positive differences. Asghar et al. (2012) stated that it captures the fact that Pakistan's economy was subject to high growth rate due to controllable levels of fiscal deficit, stabilized exchange rate, lower debt ratios and decrease in poverty ratio.

In 2008, the difference between revised and real GDP, final and real GDP is minimum as compared to other negative differences. The Pakistan Economic survey, 2008, reported that it captures the fact that Pakistan's economy was subject to undergo adverse external and internal shocks. For example, internal shocks that lower the growth were adverse supply shock, unfavorable political conditions and instability in law and order condition, deficit in current and fiscal account as well as coupled with external shocks and suffered from global recession, global financial crises, and rise in global price level of food and energy.

4.4. Graph of Differences of Real, Revised and Final Inflation

In this section, we have presented the graphical analysis of differences between real, revised and final inflation from the time period of 1974 to 2016. The graph of differences between real, revised and final inflation is given below.

The Figure 2 shows that over sample period from 1974 to 1986 the differences between revised and real inflation, final and real inflation, final and revised inflation are minimum. It shows that over the time period from 1974-1998 difference between revised and real inflation is negative. It indicates that real inflation was overstated, on average over this sample period inflation is revised in negative direction.

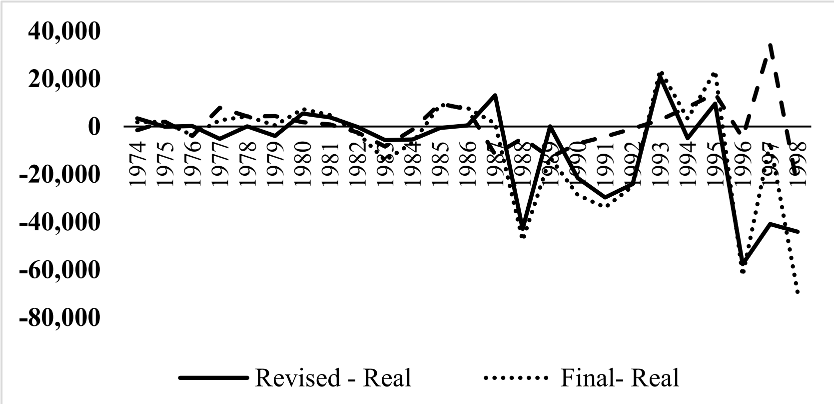

Figure 2: Differences of Real, Revised and Final Inflation

It shows that over sub sample period from 1974 to 1986 the difference between final and real inflation is positive. It indicates that real inflation was understated, on average over this time period inflation is revised in positive direction. On the other hand, over the subsamples from 1987-1998 mostly the difference between final and real inflation is negative, which indicates real inflation was overstated, on average over this time period inflation is revised in negative direction. It shows that over the time period from 1974 to 1998 the difference between final and revised inflation is positive, which indicates that revised inflation was understated, on average over this time period inflation is revised in positive direction.

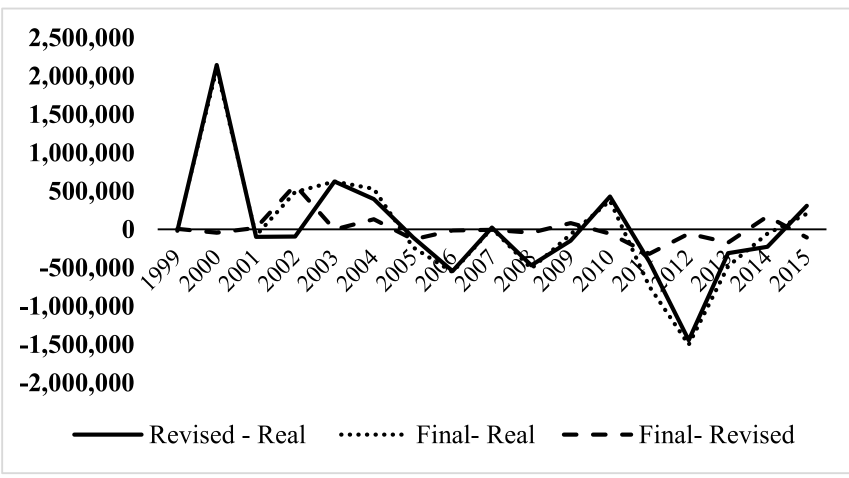

Figure 3: Differences of Real, Revised and Final Inflation

The Figure 3 shows that over sub-sample period from 1999 to 2005 mostly the difference between revised and real inflation is positive. It indicates real-time inflation was understated, on average over this sample period inflation is revised in positive direction. On the other hand, over the time period from 2006-2016, mostly the difference between revised and real inflation is negative. It indicates real-time inflation was overstated, on average over this time period inflation is revised in negative direction.

It shows that over subsample period from 1999 to 2005, mostly the difference between final and real inflation is positive, which indicates that real inflation was understated, on average over this time period inflation is revised in positive direction. On the other hand, over the subsamples from 2006-2016, mostly the difference between final and real inflation is negative, which indicates that real-time inflation was overstated, on average over this time period inflation is revised in negative direction.

It shows that over the time period from 1999 to 2005, mostly the difference between final and revised inflation is positive, which indicates that revised inflation was understated, on average over this time period inflation is revised in positive direction. On the other hand, over the time period from 2006-2016, mostly the difference between final and revised inflation is negative, which indicates that revised inflation was overstated, on average over this time period inflation is revised in negative direction.

After 1998 to 2016, the difference between revised and real inflation, final and real inflation, final and revised inflation is unstable as compared to previous time span. It captures the fact that Pakistan's economy was subject to external and internal shocks. For example, it was suffered from political instability, global recession, drought, global financial crises, deficit in current and fiscal account, and dependence on imported goods. The Pakistan economic survey 2016 reported that in recent years 2013 to 2016, the inflation level has been declined due to stable exchange rate, decrease in global goods and oil prices, proper check and control of prices by price control authority.

4.5. Forecast Evaluation

We have assessed relative forecasting performance of different models and macroeconomic conditions with reference to data e.g. real, revised and final inflation. We have used Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) to compare the forecast accuracy. The values of RMSE and MAE for Naive, ARIMA, PC and PC-TAR a model are given in following tables:

Table 3: Forecasting Results of Real Inflation for 1 Step Ahead Forecast

Models	RMSE	MAE
Naive	3.765	2.895
ARIMA	6.556	5.374
PC	6.067	5.397
PC TAR	5.566	4.754

Table 3 shows the results of one-step ahead out-of-sample forecast with real time inflation. Both forecasting accuracy measures show that RMSE and MAE of Naive are less than the other models, which indicates that Naive model better forecasts inflation than the other models.

Table 4: Forecasting Results of Real Inflation for 2 Step Ahead Forecast

Models	RMSE	MAE
Naive	3.760	2.863
ARIMA	4.704	3.326
PC	4.194	2.966
PC TAR	3.948	2.792

Table 4 shows the results of two-step ahead out-of-sample forecast with real-time inflation. According to RMSE Naive model better forecasts inflation than the other models. Whereas, on the other hand, MAE shows that Philips curve (TAR) model is most superior to other models.

Table 5: Forecasting Results of Revised Inflation for 1 Step Ahead Forecast

Models	RMSE	MAE
Naive	3.054	2.344
ARIMA	5.349	4.005
PC	4.324	4.185
PC TAR	4.321	4.185

Table 5 shows the results of one-step ahead out-of-sample forecast with revised inflation. Both forecasting accuracy measures show that the values of RMSE and MAE of Naive model are less than the other models, which indicate that Naive model better forecasts inflation than the other models.

Table 6: Forecasting Results of Revised Inflation for 2 Step Ahead Forecast

Models	RMSE	MAE
Naive	3.054	2.315
ARIMA	5.488	3.884
PC	6.249	4.418
PC TAR	6.187	4.374

Table 6 shows the results of two-step ahead out-of-sample forecast with revised inflation. Both forecasting accuracy measures show RMSE and MAE of Naive model are less than the other models, which indicates that Naive model better forecasts inflation than the other models.

Table 7: Forecasting Results of Final Inflation 1 Step Ahead Forecast

Models	RMSE	MAE
Naive	2.987	2.293
ARIMA	5.174	5.103
PC	5.426	4.615
PC TAR	5.471	4.668

Table 7 shows the results of one-step ahead out-of-sample forecasts with final inflation. Both forecasting accuracy measures show that RMSE and MAE of Naive model are less than the other models, which indicates that Naive model better forecast inflation than the other models.

Table 8: Forecasting Results of Final Inflation 2 Step Ahead Forecast

Models	RMSE	MAE
Naive	3.024	2.339
ARMA	7.704	5.456
PC	6.176	4.367
PC TAR	6.217	4.396

Table 8 shows the results of two-step ahead out-of-sample forecasts with final inflation. Both forecasting accuracy measures show that RMSE and MAE of Naive model are less than the other models, which indicates that Naive model better forecasts inflation than the other models.

5. Conclusions

Inflation forecasting is an important job for monetary policy makers because they need to keep it balanced as it affects the economic agents. Inflation decreases the purchasing power of consumers and reduce the profits of firms. In order to keep control over inflation, we need to forecast inflation by appropriate econometric model. Therefore, we have explored that which model better forecasts inflation under different macro-economic conditions with reference to data (real, revised and final data). For this purpose, we have utilized different models, which are naive model, ARIMA model, Philips curve model and Philips curve (TAR) model.

We have used annual real time, revised and final time series data from 1974 to 2016. We have accomplished this task from one and two year ahead out of sample forecasting by using rolling window. We have considered the Philips curve model with backward looking expectations and output gap. However, Philips curve (TAR) is extended by the addition of threshold level of output gap. We have selected superior and proper model on the basis of their forecasting performance. For the measurement of forecasting performance, we have used RMSE and MAE as a criterion.

We concluded that for one-year ahead out-of-sample forecasting according to real-time, revised and final data, both forecasting accuracy measures (RMSE and MAE) show Naive model is most superior to other models. However, by using real-time data for two years ahead out-of-sample forecasting, RMSE shows that Naive model is most superior to other models whereas MAE shows that Philips curve (TAR) model is most superior to the other models. On the other hand, by using revised and final data both forecasting accuracy measures show that Naive model is most superior to other models.

6. Policy Recommendations

One of the important goals of policy makers is to keep the inflation level under control. Therefore, here, the need of inflation forecasting arises which let the policy makers and researchers to predict and portray it. In case of Pakistan, we suggest that for 1 year ahead out-of-sample inflation forecasting under real-time, revised and final data naive model can be used. On the other hand, f 2 years ahead out-of-sample inflation forecasting under revised and final data naive model can be used whereas under real-time data naive and Philips curve (TAR) model can be used.

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References

Afzal, M., Rehman, H. U., & Butt, A. R. (2002). Forecasting: A dilemma of modules (A comparison of theory based and theory free approaches). *Pakistan Economic and Social Review*, *40*(1), 1–18. https://www.jstor.org/stable/25825233.

Alles, L., & Horton, D. (1999). An evaluation of alternative methods of forecasting Australian inflation. *Australian Economic Review*, *32*(3), 237–248. https://doi.org/10.1111/1467-8462.00111.

Ang, A., Bekaert, G., & Wei, M. (2007). Do macro variables, asset markets, or surveys forecast inflation better?. *Journal of Monetary Economics*, *54*(4), 1163–1212. https://doi.org/10.1016/j.jmoneco.2006.04.006.

Asghar, N., Awan, A., & Rehman, H. (2012). Human capital and economic growth in Pakistan: A cointegration and causality analysis. *International Journal of Economics and Finance*, *4*(4), 135–147. https://doi.org/10.5539/ijef.v4n4p135.

Atkenson, A., & Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation? *Federal Reserve Bank of Minneapolis Quarterly Review*, *25*(1), 2-11. https://doi.org/10.21034/qr.2511.

Bokhari, S. M., & Feridun, M. (2006). Forecasting inflation through econometric models: An empirical study on Pakistani data. *Doğuş Üniversitesi Dergisi, 7*(1), 39–47. https://doi.org/10.31671/dogus.2019.260.

Bokil, M., & Schimmelpfennig, A. (2005). *Three attempts at inflation forecasting in Pakistan* (Vol.5). Washington, D.C., United States: International Monetary Fund.

Croushore, D., & Stark, T. (2003). A real-time data set for macroeconomists: Does the data vintage matter? The *Review of Economics and Statistics*, *85*(3), 605–617. https://doi.org/10.1162/003465303322369759.

Dotsey, M., & Stark, T. (2005). The relationship between capacity utilization and inflation. *Federal Reserve Bank of Philadelphia Business Review*, 2, 8–17.

Dotsey, M., Fujita, S., & Stark, T. (2018). Do Phillips curves conditionally help to forecast inflation? *International Journal of Central Banking, September*, *14*(4), 43-92.

Fisher, J. D., Te Liu, C., & Zhou, R. (2002). When can we forecast inflation? *Economic Perspectives*, *26*(1), 32–44.

Fuhrer, J. C., & Olivei, G. (2010). *The role of expectations and output in the inflation process: An empirical assessment* (Public Policy Brief). Federal Reserve Bank of Boston. Retrieved from https://ideas.repec.org/a/fip/fedbpb/y2010n10-2.html.

Hafer, R. W., & Hein, S. E. (1990). Forecasting inflation using interest-rate and time-series models: Some international evidence. *Journal of Business*, *63*(1), 1–17.

Haider, A., & Hanif, M. N. (2009). Inflation forecasting in Pakistan using artificial neural networks. *Pakistan Economic and Social Review*, *47*(1), 123–138.

Hanif, M. N., & Malik, M. J. (2015). Evaluating performance of inflation forecasting models of Pakistan. *SBP Research Bulletin, 11*(1), 1–37.

Jahan, S., & Mahmud, A. S. (2013). What is the output gap. *Finance & Development*, *50*(3), 38–39.

Kanyama, I. K., & Thobejane, B. M. (2013). *Forecasting macroeconomic variables in South Africa: Parametric vs. non-parametric methods*. Department of Economics and Econometrics, University of Johannesburg. http://www.essa2013.org.za/fullpaper/essa2013_2716.pdf

Khan, M. M. S., & Schimmelpfennig, M. A. (2006). *Inflation in Pakistan: Money or wheat?* (Working Paper No. 06/60). International Monetary Fund.

Önder, A. Ö. (2004). Forecasting inflation in emerging markets by using the Phillips curve and alternative time series models. *Emerging Markets Finance and Trade*, *40*(2), 71–82. https://doi.org/10.1080/1540496X.2004.11052566.

Orphanides, A., & Van Norden, S. (2005). The reliability of inflation forecasts based on output gap estimates in real time. *Journal of Money, Credit and Banking*, *37*(3), 583–601.

Rees, A. (1970). The Phillips curve as a menu for policy choice. *Economica*, *37*(147), 227–238.

Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of Monetary Economics*, *44*(2), 293–335. https://doi.org/10.1016/S0304-3932(99)00027-6.

Stock, J. H., & Watson, M. W. (2007). Why has US inflation become harder to forecast? *Journal of Money, Credit and Banking*, *39*, 3–33. https://doi.org/10.1111/j.1538-4616.2007.00014.x.

Stock, J. H., & Watson, M. W. (2008). *Phillips curve inflation forecasts* (NBER Working Paper No. 14322). National Bureau of Economic Research. https://doi.org/10.3386/w14322.

Sultana, K., Rahim, A., Moin, N., Aman, S., & Ghauri, S. P. (2013). Forecasting inflation and economic growth of Pakistan by using two time series methods. *International Journal of Business and Economics Research*, *2*(6), 174–178. https://doi.org/10.11648/j.ijber.20130206.17.

Swanson, N. (1996). Forecasting using first-available versus fully revised economic time-series data. *Studies in Nonlinear Dynamics & Econometrics*, *1*(1), 1–20.

Yellen, J. L. (2015, September 24). *Inflation dynamics and monetary policy* [Speech]. Amherst, Massachusetts, MA: University of Massachusetts. https://doi.org/10.2202/1558-3708.1012.

Zardi, S. C. (2017). *Forecasting inflation in a macroeconomic framework: An application to Tunisia* (Working Paper No. 07-2017). Graduate Institute of International and Development Studies Working Paper.

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