Evaluating Performance of Inflation Forecasting Models of Pakistan

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Abstract

This study compares the forecasting performance of various models of inflation for a developing country estimated over the period of last two decades. Performance is measured at different forecast horizons (up to 24 months ahead) and for different time periods when inflation is low, high and moderate (in the context of Pakistan economy). Performance is considered relative to the best amongst the three usually used forecast evaluation benchmarks – random walk, ARIMA and AR(1) models. We find forecasts from ARDL modeling and certain combinations of point forecasts better than the best benchmark model, the random walk model, as well as structural VAR and Bayesian VAR models for forecasting inflation for Pakistan. For low inflation regime, upper trimmed average of the point forecasts out performs any model based forecasting for short period of time. For longer period, use of an ARDL model is the best choice. For moderate inflation regime different ways to average various models' point forecasts turn out to be the best for all inflation forecasting horizons. The most important case of high inflation regime was best forecasted by ARDL approach for all the periods up to 24 months ahead. In overall, we can say that forecasting performance of different approaches is state dependent for the case of developing countries, like Pakistan, where inflation is occasionally high and volatile.

Key Words: *Inflation, Forecast Evaluation, Random Walk model, AR(1) model, ARIMA model, ARDL model, Structural VAR model, Bayesian VAR model, Trimmed Average.*

1. Introduction

Monetary policy is more effective when it is forward looking (Faust and Wright (2013) and Svensson (2005)). Central banks forecast inflation considering all possible relevant factors. State Bank of Pakistan (being central bank of the country) can only have some control[2] over the future inflation. This raises the prominence of inflation forecasting in monetary policy making[3]. We understand, inflation forecasts are the main critical input in the deliberations pertaining to the monetary policy decisions of SBP[4]. In its annual report on the state of economy, SBP publishes its inflation forecast for the upcoming fiscal year but, mostly, different from the target given by the government[5]. SBP started publishing its

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[2] 'Some' rather than the perfect control. It is because of the fact that during the 'lag period' [which was found to be up to 24 months in a case study of Pakistan by Qayyum et al (2005) over the period of 1991:03 to 2004:12] between monetary policy action and its results, 'other' variables also affect inflation in Pakistan; like in other developing countries, in particular. Such 'other' variables include fiscal decisions (like changes in sales tax rate and/or the financing 'mix' of the budget deficit) of the government, internal factors (such as local supply shocks like floods in Pakistan in 2009), external factors (such as global commodity price shock like that of 2008) and inflation expectations etc.

[3] Inflation forecasting is of immense importance to households and businesses as well.

[4] In addition to the results of inflation expectations (telephonic) survey conducted every two months by Research Department of SBP. For details see SBP Annual Report on the state of Pakistan economy for the year 2012-13.

[5] The government of Pakistan announces its target for inflation (and economic growth) in its annual development plan which is released just before the annual budget presentation in the Parliament. And, there is a gap of almost 5 to 6 months in the announcement of the inflation target and the publication of SBP annual report. It helps SBP to better see the inflation at the year end. SBP also publishes its inflation forecast in its quarterly reports (on the state of economy of the country). SBP does not provide any detail about its inflation forecasting approaches/models, however.

inflation forecast regularly only from FY2005-06. How good are Pakistan's inflation forecast, is the research question of this study. [Inflation] forecast needs to be good in order to be useful in [monetary policy] decision making process (Clark and McCracken, 2011). In figure 1 (of Appendix) we show the government inflation target, SBP forecast for annual inflation and the observed annual (12 month average) inflation; for the years for which we could find the (numerical) inflation target in the government's relevant documents. SBP inflation forecasts are closer to observed inflation, while targets differ significantly. Of course, there are different approaches/models to forecast inflation. Establishing which approach/model forecasts Pakistan's inflation in a better way involves formal evaluation of resultant forecasts.

There is no dearth of literature on exploring what determines inflation and on forecasting inflation. But relatively less number of studies have attempted to evaluate the inflation forecasts. Those which are prominent include Bokil and Schimmelpfennig (2006), Bukhari and Feridun (2006), Haider and Hanif (2009), and Riaz (2012) for the case of Pakistan; and Atkeson and Ohanian (2001), Elliot and Timmermann (2008), Stock and Watson (2008), Norman and Richards (2012), and Antipin et al (2014) for the case of developed countries like US and Australia[6]. Rather than going into the details we would like to opine that even in the case of forecast evaluation with reference to developed countries like US (see for example, Atkeson and Ohanian, 2001), most of the studies focused upon overall inflation regime except a few like Stock and Watson (2008). Stock and Watson (2008) found the performance of inflation forecasting models to be episodic; and different models are found to be the best performing for different time periods. However, none of earlier studies on Pakistan have attempted to provide point inflation forecast evaluation for different inflation regimes like low, medium and high inflation periods. Furthermore, these different studies have used different modeling approaches to forecast inflation. These include single equation models, vector autoregression models and some sort of leading indicator models. To the best of our knowledge, no one has compared various models in a single study. In this paper, considering varying inflation environment, as is in developing countries, and suitability of different approaches to model inflation when there are competing inflation determinants; we have evaluated point inflation forecasts from different models, and from different approaches to combine model based forecasts. To the best of our knowledge, ours is the first study which uses one-sided trimmed averaging to combine inflation forecasts in case of a developing country to see if such averaging works best during extreme inflation periods. We evaluate these forecasts to arrive at some guidance for decision makers about the appropriate approaches, under specific inflation regime, to rely on inflation forecast.

Inflation in Pakistan has, in the recent past, been higher and more volatile (in absolute sense) making a difficult job of forecasting even more difficult[7]. By analyzing the monthly inflation data for the last two decades (July 1992 to June 2014[8]); we classify the inflation in Pakistan in three regimes: low, high, and moderate. In this study we have estimated various time series models of inflation in Pakistan

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[6] For summary of a few selected studies see Appendix.
[7] Pakistan just ended a first five (consecutive) year period (FY08 to FY12) of double digit inflation in the country's history (since 1947).
[8] Fiscal year in Pakistan runs from July to June.

for the purpose of forecasting inflation[9] and evaluating the forecast ability of these estimated models, and 'forecast combinations' there from, for (i) different horizons (3 months to 24 months ahead) and (ii) for different inflation regimes (low, high, and moderate). These regimes are obtained on the basis of Zeileis et al (2003) structural change test and reported in the table 1 (d) of appendix. Considering the sample size we test for maximum two breaks splitting the data in three regimes and selection is based on Bayesian Information Criterion.

Rest of the paper is organized as follows. In the next section we discuss about the measure of inflation we use to model for forecasting. Then we spell out the models we have estimated to forecast inflation for Pakistan economy and describe the data and methodology used. In section 4 we compare the performance of these estimated models generating pseudo out of sample (unconditional) point forecast for inflation in Pakistan in varying inflationary environment – low, moderate and high[10]; and for different horizons ahead. In the final section we conclude.

2. Choosing Measure of Inflation to Forecast

Modeling inflation entails the basic question: which measure of inflation we should choose to model for forecasting? In Pakistan, we have different measures of general trend in prices in the country. Pakistan Bureau of Statistics (PBS), the national statistical agency, is responsible for collection, compilation and dissemination of prices related data/indices. Such indices include GDP deflator, Consumer Price Index (CPI), Wholesale Price Index (WPI) and Sensitive Price Index (SPI). Within the basket of CPI, we also have an exclusion based measures of core prices index and that is for Non-Food Non-Energy (NFNE) group. Another measure of core inflation for which PBS has recently started publishing data is '20 percent trimmed core inflation'. In calculating '20 percent trimmed core inflation', 10 percent of items showing extreme price changes each from top and bottom are excluded from the CPI basket.

SPI is the most frequently available price index but it covers only necessities and just 17 cities. GDP deflator is the most comprehensive one but is available less frequently. WPI does not cover the services, however. Core inflation is the one measure which SBP considers important in discussion in its flagship publications; but it is not the target inflation variable. So we are left with CPI. Government of Pakistan announces annual inflation target which is basically for '12 month average of Year on Year (YoY) change in CPI'. In this study, by inflation we mean YoY change in the CPI.

3. **Models, Dataset and Methodology**

In order to have accurate forecast of inflation we need to understand what best explains the inflation. Theoretically there are various explanations to the macro level behaviour of inflation including the quantity theory of money; Phillips curve; and structuralists' explanation of inflation. The contribution of (broad) money growth in inflation in Pakistan (as has been documented by Nasim (1997),

[9] Which should, in any way, not be considered as inflation forecasting models of the State Bank of Pakistan.
[10] See Table 1 (b) of Appendix for the levels of low, medium and high inflation in the context of Pakistan.

Hanif and Batool (2006), Riazuddin (2008) etc), relationship between output gap and inflation (as reported by Bukhari and Khan, 2008), and structuralists' explanation of inflation in the context of developing countries like Pakistan (as discussed in Bilqees, 1988) deserve attention to make inflation forecasts. While exploring the role of supply and demand shocks as drivers of inflation, Khan and Hanif (2012) suggested that in addition to monetary factors, supply side disturbances should also be taken into account for better understanding of, and 'handle' on inflation in Pakistan.

Obviously, all the relevant forces cannot be modeled in one framework. We have used different approaches to see what explains inflation in different competing empirical models. These include single equation as well as multiple equations models. For single equation modeling we have used ARDL approach. For the case of multivariate time series analysis we have used Sims' (1980) vector autoregression (VAR) approach. Expecting improvement in forecast accuracy, the VAR models have also been estimated using Bayesian approach. We know that the number of coefficients to be estimated, even for a moderate VAR, is large and thus usual (maximum likelihood) estimates may not have desirable properties. If we apply, however, Bayesian estimation, better accuracy is expected due to a reasonable reduction in the parameters to be estimated and thus we can expect improved forecast accuracy (see Canova (2007), Robertson (2000) for details) from Bayesian VAR forecasts.

We do not expect all the variables in this study[11] to be integrated of order 1; rather we will have a set of variables which are mixture of stationary and non-stationary variables. We will take difference of non-stationary variables and consider the stationary variables in levels following the practice in the literature. Forecasts based upon first differencing approach would be robust to (unobserved) shifts (Hendry and Clements, 2003); if any, during the estimation period.

Before going into the empirical results from the estimated models, a few words on conceptual framework of each of these models are necessary.

3.1 Single Equation Inflation Forecasting Models

The simple monetarist model is based on the quantity theory of money. We can say that there is a positive relationship between changes in money supply and the inflation in the long run. According to most of the studies, inflation in Pakistan has been a monetary phenomenon. For example, Riazuddin (2008) has explored how money growth has interacted historically with inflation in Pakistan and found inflation to be a monetary phenomenon. He found that three-fourths times high (low) broad money growth was followed by high (low) inflation next year during the period of his study (1958-2007). We ourselves have observed this; though in different manner: as far back as we can find the information on the annual targets of money supply growth and those of inflation in the history of Pakistan, we observe that any deviation from the target money growth (money surprise) has resulted in deviation from inflation target (inflation surprise) next year (see figure 2 in Appendix). This also suggests the Monetarists' proposition and thus one can say that inflation is mostly a monetary phenomenon in Pakistan. While modeling inflation, in addition to broad money supply growth, we also consider

[11] For the list of variables used in this study, see Table 1(c) of Appendix.

weighted average lending rate (WALR) charged by the commercial banks to the private sector (borrowings).

Following the inflation-unemployment relationship (the Phillips Curve), we can say that a positive output gap[12] indicates that inflation is building up in the economy and a negative output gap suggests disinflation (or even deflation) is approaching. Interestingly, output gap has also served the role of a 'leading indicator for inflation in Pakistan since 1951[13]. Before deciding on how to get output we need to think of what is best proxy for output on monthly basis. Here, in this study, we consider large scale manufacturing (LSM) production as proxy for output for the period of study (July 1992 to June 2014)[14].

From the supply side factors, the most important variable which determines inflation in Pakistan is the global commodity prices, as one quarter of inputs in the manufacturing sector of Pakistan are imported (Choudhary et al, 2012). Amongst the global commodities, the most important is the crude oil which historically constitutes one-third of overall import bill of Pakistan. Petroleum products' prices are important as these affect the CPI inflation directly (being part of its basket) as well as indirectly (as it affects the cost of production – through electricity prices and transportation fares) in the country. Inflation related expectations also play their role in inflation dynamics. Particularly, observed inflation is found to follow the inflations expectations path in Pakistan at least in recent times[15]. In case of developing countries, particularly Pakistan, we do not have long time series pertaining to inflation expectations of people[16]. However, we can also proxy inflation expectations using oil prices because fuel prices are observed to play a major role in the 'formation of inflation expectation in Pakistan' in the 'SBP-IBA inflation expectations survey' as found in Abbas, Beg, and Choudhary (2015). Considering its importance, we can use global crude oil price in modeling inflation for Pakistan. We estimate an inflation forecasting model comprising output gap, changes in oil price[17], WALR, and M2 growth along with inflation inertia. The lagged terms of inflation captures the inflation persistence which has been documented in the literature as one of the features of inflation in Pakistan (See Hanif et al 2012).

We have used autoregressive distributed lag (ARDL) modeling for estimation of the single equation models. Considering the lags in the transmission mechanism of monetary policy (as well as other)

[12] The difference between level of output produced by the country and the potential (which we proxy by estimating trend use Hodrick-Prescott (1997) filter) of the economy is called output gap.

[13] If we look at the figure 3 of the Appendix, we can see negative relation between inflation and unemployment. If we look at figure 4 we can point out that when output gap was 'positive or expanding' ('negative or shrinking') more than three out of four times inflation increased (decreased) in Pakistan in the following year. While doing this (satellite) analysis for Pakistan economy upon annual data from 1951 to 2013; the output gap is measured by the percent deviation observed overall real GDP from its potential GDP and inflation is measured by the 12 month average of YoY change in CPI.

[14] There are various reasons to consider LSM instead of overall observed GDP. We know in case of developing countries we do not have output data at higher frequency (like quarterly / monthly) and thus we need to proxy output with some relevant variable for which high frequency data is available. Second reason pertains to the fact that in developing countries it is the industrial sector which is main user of the banks' credit. Lastly, manufacturing industry has backward (with agriculture sector) and forward (with services sector) linkages in Pakistan. Thus it can be used as a proxy for overall economic activity in the country

[15] SBP Annual Report for FY13

[16] SBP-IBA telephone survey on inflation expectation of households is only a recent attempt in this context.

[17] It is local currency oil price index (so that exchange rate need not to be incorporated separately in this model).

variables in affecting inflation in the country, we utilized up to 13 lags in this type of modeling except for broad money growth. For board money growth we have used up to 24 lags in the model selection process[18]. Within these maximum lags, the actual lag selection has been done on the basis of Akaike (1974) information criterion. We name this first model as an ARDL1. For details, see Appendix.

We know that it is not only the petroleum products' prices which matter, prices of other international commodities, like food, also matter in determining general price level in developing countries like Pakistan[19]. What matters more – global crude oil prices or overall international commodity prices - is an empirical question. Thus, we have estimated another structural equation model which we name 'ARDL2' by considering world consumer price index. It is not only the international commodity price changes which impact the general price level in the importing country, but the changes in country's exchange rate may also have implications for domestic inflation as it is the local currency price which is accounted for in the various price indices compiled by the national statistical agencies. In the case of a developing country like Pakistan where households anchor their inflationary outlook to retail petroleum prices (which are direct function of global crude oil prices) and commercial enterprises focus on the current and (expected) future value of the Pak Rupee[20]; we need to consider both the overall global commodity prices index (inclusive of international crude oil prices) and exchange rate, Pak Rupees per US dollar[21], as determinants of inflation in the country. Rather than focusing upon the output gap (as in ARDL1), in this (another) model we directly consider the (industrial) production in the country. Thus, ARDL2 estimates inflation as function of changes in 'overall global commodity prices index', domestic industrial production growth, growth in broad money demand, and depreciation / appreciation of 'Pak Rupee / US dollar parity'. For details, see Appendix.

3.2 Multiple Equations Inflation Forecasting VAR Models

Now we move towards multiple equations models. We use Sims (1992) like VAR models. These are, again, based upon the variables which are found significant in the existing empirical literature pertaining to inflation in Pakistan. Since we have used relevant economic theory in defining the relationships amongst the variables modeled to forecast inflation; the joint dynamics of variables are represented by structural VAR modeling. We can classify the earlier work on Pakistan [like by Khan and Schimmelpfennig (2006), Agha et al (2005)] into a monetary structural VAR model (MVAR), a credit structural VAR model (CVAR) and external structural VAR (EVAR) model. We can use these VAR models separately as well as in a comprehensive way.

[18] For example, according to Qayyum et al (2005) monetary expansion/contractions take up to 24 months to impact inflation in Pakistan. In another study, Choudhary et al 2011 reported in the price setting survey of Pakistani firms that complete pass through of petroleum prices reaches Pakistani products prices after 9 months.

[19] See for example Hanif 2012 for detailed links of global food price changes and food inflation in Pakistan. The share of imported goods in total consumption in Pakistan is one-fifth (Ali, 2014).

[20] SBP Annual Report on the state of (Pakistan) economy, for FY13, page 4.

[21] Almost 90 percent of international trade transactions of Pakistan are denominated in US dollars.

3.2.1 *Monetary Aggregates Focused Inflation Forecasting VAR Models*

Khan and Schimmelpfennig (2006) explored a simple monetary model where economic agents are assumed to hold money for transaction purposes, as a store of value and speculative purpose. Assuming velocity of money to be constant; inflation results if money growth exceeds the nominal income growth. But, is it the price channel or the quantity channel of monetary transmission mechanism which work through the economy to attempt achieve inflation target? Before the period under study, Pakistan had been explicitly using monetary aggregate targeting to maintain monetary stability in the country. Country started financial sector reforms and restructuring including the areas of monetary management. SBP transitioned from direct instruments to indirect instruments of monetary management in the country. After some transition period in the 1990s, Pakistan abandoned monetary aggregate targeting in late 2000s and moved towards use of changes in short term interest rate (called discount rate or more specifically 3-days reverse repo rate in Pakistan) to achieve price stability (without being prejudice to economic growth). But, Pakistan's departure from monetary aggregates targeting and formal use of changes in 3-days reverse repo rate to signal monetary policy stance does not necessarily mean that monetary aggregates have no use in predicting future inflation in the country. An increase in discount rate (policy rate of the central bank) increases the weighted average lending rates (charged by commercial banks to private borrowers) and reduces demand for money and thus inflation. That simply means: (i) discount rate (DISR) is exogenous to the system and thus affects all disturbances (in weighted average lending rates (WALR), growth in reserve money (M0), growth in broad money (M2)[22] and inflation); (ii) weighted average lending rates (WALR) affect all variables in the system other than the discount rate; (iii) growth in reserve money affects the disturbances in broad money growth and inflation, (iv) Growth in broad money affect the disturbances of inflation, and (v) Inflation does not affect the disturbances of any other variable in the system. We call this as MVAR1 model. We can see that we do not consider the income here in MVAR1 model. We have also estimated another monetary VAR model where we bring in the representation of real sector by putting output gap before inflation (and exclude the WALR). We call this MVAR2 model. These MVAR models are also explained in the Appendix.

3.2.2 *Credit Focused Inflation Forecasting VAR Models*

Credit channel is considered as an important channel of monetary policy transmission mechanism. Bernanke and Blinder (1988) has constructed a theoretical model for studying the impact of this channel on economy. A version of this model with slight changes is constructed by Montes and Machado (2013) for a developing country and finds that supply of credits affects both employment and output gap and thus has an impact on inflation. While studying the relative importance of various monetary policy channels for Pakistan, Agha et al (2005) observed that, over the period of their study, commercial banks played a major role in monetary policy transmission mechanism with private sector credit as the leading indicator as it affected aggregate demand (and thus inflation) in the country. While studying the role of credit market frictions in the transmission of monetary shocks in Pakistan,

[22] Following Kapetanios et al (2007) we have considered both the high powered money as the broad money in this monetary VAR model.

Choudhary et al (2012) also found support of the view that existence of credit channel is relevant for developing economies. Thus, to consider the role of private sector credit we also build a private credit based structural VAR model for forecasting inflation in Pakistan. Being a developing country we know that government also borrows from banking system to finance its budget deficit. We observe that, at times, government borrowing from banking system serves as a leading indicator of inflation in Pakistan[23]. In addition to role of government borrowing (for budgetary spending) in boosting consumption, government borrowing for financing the budget deficit also anchors the inflationary expectations in developing countries like Pakistan. Thus, along with the private sector credit and (related) weighted average lending rate, we have also considered government borrowing (from the banking system) and related interest rate (T-bill rate) to predict inflation in Pakistan. The recursive structure of this credit structural VAR (CVAR) model assumes: (i) discount rate is exogenous to the system and thus affects all disturbances in T-Bill Rates (TBLR), growth in public sector borrowing (GPSB), weighted average lending rate, growth in private sector credit (GPSC) and inflation, (ii) T-Bill rate affect all variables in the system other than discount rate, (iii) growth in public sector borrowing affect all variables in the system other than discount rate and T-Bill rate, (iv) changes in lending rate affect the disturbances of private sector credit and inflation, (v) changes in private sector credit affect the disturbances of inflation and (vi) Inflation does not affect the disturbances of other variables in the system. We call this CVAR1 model. Again, like in monetary VAR model above, we considered another credit VAR model by incorporating large scale manufacturing growth in the country - placing it before inflation in the model. We call this CVAR2 model. Another credit VAR model is also estimated by excluding T-Bill rate from CVAR2. We call this CVAR3 model.

3.2.3 External Sector Inclusive Models for Forecasting Inflation

In the aforementioned monetary and credit based multivariate models, we can see one aspects missing in those models and that is the external sector. Now we consider external sector with and without incorporating the monetary sector. For output side of the economy, we will again consider the large scale manufacturing (LSM) production as a proxy.

There are various ways through which Pakistan economy is impacted by the external sector. These include the following: (i) Global oil prices[24]. (ii) Overall international commodity prices. (iii) Pakistanis working overseas also send significant amount of money in the form of workers' remittances to maintain their families in the country. Workers' remittances proved to be very important for Pakistan as it has been financing a significant proportion of its trade deficit since years[25] and thus helps keep balance of payments difficulties mostly. For example, during FY13 remittances financed over two-thirds of Pakistan's trade deficit. It helps pare pressures upon exchange rate and thus matters in maintaining price stability in the country. (iv) Pakistan being importer of almost one quarter of manufacturing sector intermediates; exchange rate matters for price setting behaviour of firms in the country and thus cannot

[23] At least for the case of 'non-food, non-energy, excluding house rent index (NFNENHRI)' inflation in Pakistan.
[24] Oil Price is considered as an important factor affecting inflation [and output] in an economy. Many studies have considered it including Bernanke et al (1997), and Hamilton and Herrera (2004).
[25] During the period of study (FY1993 to FY2014) Pakistan received workers' remittances of US$114.4 billion, against trade deficit of US$143.1 billion. Thus, workers' remittances financed about 80 percent of country's trade deficit during the last two decades.

be ignored in inflation forecasting model. For this purpose we have earlier considered US dollar – rupee parity in single equations modeling. What we can also consider other than the US dollar – Pak rupee parity is the real effective exchange rate of Pakistan, which actually covers the country's exchange rate policy in relatively broader manner. (v) For the exports demand of Pakistan's surplus output what matters is the global business cycle. We know US industrial output can be used as a proxy for demand for Pakistan's exports (being top most exports destination for Pakistan) as well as for the global business cycle (being largest global economy in the world at least during the period of this study).

We have considered aforementioned external sector candidate variables in three different external sector structural VAR models, differentiated mainly by the consideration of international crude oil price versus overall global commodity prices. We name these EVAR1, EVAR2, and EVAR3. In the first model we assumes that (i) movements in International crude oil prices (GOLP) are exogenous to the system and thus affects all disturbances of a) growth in foreign (US) industrial production index (GFIP), b) growth in worker's remittances (GWRM), c) changes in real effective exchange rate (CRER), d) change in industrial production of large scale manufacturing (CLSM) in Pakistan, and inflation (GCPI) in Pakistan; (ii) GFIP affects all variables in the system other than GOLP; (iii) GWRM affects all variables in the system except GOLP and GFPI, (iv) growth in real effective exchange rate affect CLSM and inflation, (v) demand pressures in the economy, gauged by changes in industrial production index of large scale manufacturing (CLSM), affect the disturbances in inflation; and (iv) inflation does not affect the disturbances of any other variables in the system.

In another setting of external VAR model, which we call EVAR2, we have considered changes in overall international commodity prices instead of crude oil price only. Other variables included here in this structural VAR model are depreciation / appreciation in nominal exchange rate (US dollar – Pak rupee parity), broad money growth, changes in large scale industrial production, and inflation[26]. The recursive structure of this model assumes that (i) world commodity prices changes (WCPC) or foreign inflation[27] is exogenous to the system and thus affects all disturbances of a) changes nominal exchange rate[28] (CNER) of the country, b) growth in broad money supply (M2) in Pakistan, c) real economic growth (proxy by CLSM) in the country, , and inflation (GCPI) in Pakistan, (ii) shocks to changes in nominal exchange rate does affect the disturbances of all other variables in the system except global inflation, (iii) Growth in broad money affect the disturbances of inflation and the change in industrial production of large scale manufacturing (CLSM) in Pakistan, (iv) shock to demand, measured by growth in industrial production of large scale manufacturing (CLSM) in Pakistan, does not affect other variables in the system except inflation, and (v) inflation does not affect the disturbances of any other variables in the system except changes in nominal exchange rate. Thus, there is consideration of bi-directional feedback: from inflation to exchange rate as well as from exchange rate to inflation in the country.

[26] This model is closer to Almounsor (2010) which is an IMF study to explore inflation dynamics in Yemen.

[27] Considering the importance of oil imports, being one-third of overall imports in Pakistan; we considered global oil prices in EVAR1 setting. However, we cannot ignore the non-oil imports as well because these are more than the oil imports and that foreign consumption constitute about 20 percent of over overall consumption in the country (Ali, 2014). Thus, here in EVAR2 we consider global inflation rather than global oil prices changes only.

[28] In terms of Pak Rupees per US dollar.

In another setting of external VAR model, we introduced SBP policy interest rate, after the global crude oil price changes and changes in global industrial production, in the EVAR1 model and we name it EVAR3 model.

3.2.4 A Comprehensive Model for Inflation Forecasting

To test the validity of the claim by Diebold and Lopez (1996) that it is always optimal to combine information for forecasting purpose (compared to combining the forecasts from different sets of inflation); we thought to considered all the monetary, fiscal, external and real sector variables in one structural VAR model, in another model, and we call this a comprehensive VAR model (CMVAR). It is specified in the following order: changes in global crude oil price, depreciation /appreciation in Pak Rupee / US Dollar parity, discount rate, growth in broad money supply, changes in large scale manufacturing and inflation. By considering the broad money supply growth we have implicitly considered the behaviour of public sector borrowing and thus fiscal sector as well; since M2 includes banking system's claims upon private as well as government sectors. In that sense of considering all the sectors of the economy we have called it comprehensive VAR model (CMVAR).

3.3 *Multiple Equations Inflation Forecasting* Bayesian VAR Models

We don't have more than 7 variables in any of the VAR models discussed above. Still we know that there can be degrees of freedom problem simply because we have monthly dataset and we initially include 13 lags at maximum along with seasonal dummies. We then decide about appropriate lag length based on Akaik (1974) information criterion. Even if we consider only the estimation of a moderate VAR, for example, 6 variables model[29] where we have to include 6 lags of each variable, we have to estimate 222 parameters. The usual ML estimates are unlikely to have good properties. This is the typical case where small sample size in real situations makes the coefficient estimation and inference imprecise. Doan, Litterman and Sims (1984) suggest the application of Bayesian procedures in the estimation of the parameters of the VAR in case of small sample size. Bayesian VAR (BVAR) improves the accuracy of estimates and subsequent forecasts by introducing appropriate prior information into the model. It is equivalent to assume a probability distribution for coefficients. An important and empirically successful example of such a prior is Minnesota prior. The Minnesota priors make the large number of parameters to depend on relatively much smaller number of hyper parameters. Minnesota (Litterman) prior is of the form where normal prior is assumed for coefficients and fixed error variance covariance matrix as estimated by OLS. Here priors are the functions of small number of hyper parameters. We need to specify these hyper parameters only. For this study we have used the benchmark (as given in Canova (2007)) values for a general tightness parameter, a decay parameter and a parameter for lags of other variables as (0.2, 1, 0.5) implying a relatively loose prior on the VAR coefficients. Bayesian methodology

[29] In the above described VAR models we have 7 variables in only one model (EVAR3). All others have at most 6 variables.

involves updating of prior distribution by sample information contained in the likelihood function to form a posterior distribution[30].

In Bayesian estimation better accuracy is expected due to a reasonable reduction in the parameters to be estimated, and thus forecast accuracy can be improved. In an assessment, Robertson (2000) has shown that VARs with Minnesota priors produce better forecasts to those of say univariate models. An important thing is that even if prior is false this approach may reduce the MSE of estimates (Canova, 2007). We have estimated aforementioned VAR models (with highest suffix) using Bayesian approach as well and named them with adding B in the prefix, that is, BMVAR, MCVAR, BEVAR, and BCMVAR.

3.4 Simple and Trimmed Averages of Forecasts

By this point we have discussed ways to forecast inflation in Pakistan by combining information ranging from single equation modeling to monetary VAR, credit VAR, external VAR, and comprehensive VAR models. We now see if we get improvement in the forecast accuracy by combining the forecasts. There are various studies which have used simple and trimmed mean approaches to combine the forecasts. Such studies include Stock and Watson (2004), Akdogan et al (2012), and Meyer and Venkatu (2014). Different models may be getting affected differently by the structural instabilities (pointed out as the biggest enemy of forecasts by Clements and Hendry, 1998) and thus averaging may improve the forecasts which are affected differently by the potential break(s). Easiest way to combine forecast is to take simple average (arithmetic mean) of forecasts obtained by different models. That is what we have used in this study. Many poor forecasts here may drag down the performance of simple averaging of the (inflation) forecast. This can be handled by using trimmed mean[31] of forecasts. In addition to simple averaging of point inflation from the aforementioned models, we have also evaluated if the trimmed[32] mean helps improve inflation forecasts in case of Pakistan. Trimmed average may be a useful tool for moderate inflation regime and may not be that useful for low or inflation regimes, however. To see if one-sided trimming[33] is useful for extreme inflation environment, we have also evaluated lower trimmed and upper trimmed means of inflation forecasts from different models.

3.5 Benchmark Models

In addition to all above models, we also estimated different models used in the literature as benchmarks for inflation forecasts evaluation. We find use of random walk or RW (like in Atkeson and Ohanian (2001)); autoregressive moving average model of integration of order 1 or ARIMA (like in Narayan and Cicarelli (1982), Claus and Claus (2002), Benkovskis (2008) and Adebiyi et al (2014)); and autoregressive model of order 1 or (AR(1) (like in Faust and Wright (2013)) as benchmark models. We

[30] There is a need to account for uncertainty about future realization of structural shocks and parameter estimation. These two sources of uncertainty are tackled in a quite straightforward way where we treat both shocks and parameters as random in Bayesian approach.
[31] Other could be to use median of forecasts from all the models.
[32] We arrange all the inflation forecasts from different models and trim 25 percent of the forecasts from each side before averaging the forecasts. Thus we average the forecasts of middle 50 percent best forecasts compared to the benchmark model's forecast.
[33] Trimming 25 percent of forecasts from one side only.

first compare all these benchmarks to see which one performs best to forecast inflation in the case of Pakistan during different inflation regimes and for different forecast horizons considered in our study. The best amongst these three benchmarks is used as a benchmark in our study to evaluate inflation forecasting through different models/approaches as described above.

The random walk (RW) model we estimate is with drift. It contains the first lag of inflation as regressor with unit coefficient. Autoregressive model of order 1, AR (1), with drift is also considered. Contrary to the RW model, the coefficient of (first) lagged regressor is estimated in an AR(1) model. In case of ARIMA model to forecast headline inflation for Pakistan, the model is finalized based upon Akaike Information Criterion (AIC); after selecting the order of differencing for both seasonal and non seasonal unit roots. Since we have used monthly data frequency, the estimated ARIMA model is allowed to include seasonal AR and MA terms.

The dataset used is from Jul 1992 to June 2014. Dividing the dataset in two halves, the models are first estimated up to June 2002 and forecasted from July 2002 to June 2004 that is form one month ahead to 24 months ahead[34] and then one data point is increased and same process is repeated and so on. We calculate RMSE and relative RMSE (RRMSE) for different forecast horizons. The RRMSE is calculated relative to the best benchmark model which makes the comparison of different models meaningful. The value of RRMSE less than unit for any estimated model implies that its forecast performance is better than the benchmark model; and a value greater than unity implies otherwise.

As we highlighted in the figure 1 (in the appendix), there was significant impact of global commodity prices shock of 2008 upon inflation in Pakistan when it converted from single digit level to double digits. Thus, it is important to check if there are breaks in the time series data for inflation in Pakistan during the study period. We found two breaks one at Dec 2007 and second at Jul 2009. For dating the structural break(s) we followed Zeileis et al (2003) dynamic programming algorithm.

Using these two breaks points, we have divided overall period studied in the paper as low, high and moderate inflation regimes[35]. In addition to looking at the relative performance of different models (relative to the best benchmark model) considered in this study for forecasting inflation in Pakistan; we have also looked into their comparative performance under different inflation regimes: low, high and moderate.

4. Pseudo Out of Sample Forecast Performance

Pseudo out of sample point forecast performance is reported in the Tables 2(a) through 2(c) of the appendix for low, high and moderate inflation environment. The numbers in these tables are root mean square errors (RMSE) relative the ‘best’ benchmark model. It is common practice in applied econometrics literature to compare the forecasting performance of different forecasting models relative to some benchmark model. Which model is to serve as the benchmark model here? There are various models, ranging from RW, ARIMA to AR(1) model, reported in the literature and used as benchmark

[34] The length of the forecast horizon largely depends upon the how long the changes in policy instruments take to affect the inflation (and economic growth, if any) in the country. Such period (known as ‘lag period’ in the literature) has been found to be 24 months (see Qayyum et al, 2005).

[35] For mean inflation levels during different inflation regimes, see Table 1 (b) of the appendix.

model for forecasts evaluation. We have first checked which of these three approaches generates best inflation forecasts for Pakistan. We find that none of the ARIMA and AR(1) is able to beat random walk approach for forecasting inflation for Pakistan during period of this study. Now we are going to compare the performance of the various inflation forecasting approaches against the RW model; which we find as the best one, amongst the usually used benchmarks, for the case of inflation forecasting in a developing country like Pakistan.

Row (i) of Tables 2(a) through 2(c) contains forecast horizon period (h). Forecast horizons are reported from 3 to 24 months ahead, with an interval of 3 months. Rows (ii) to (xvi) contain relative RMSE for ARDL1, ARDL2, MVAR1, MVAR2, CVAR1, CVAR2, CVAR3, EVAR1, EVAR2, EVAR3, CMVAR, BMVAR, BEVAR, BCVAR, and BCMBVAR models respectively. In the rows (xvii) of these tables we have reported relative RMSE pertaining to inflation forecasts based upon the 'simple average' of all the 15 models. Below this, we have reported row (xviii) which contains relative RMSE pertaining to inflation forecasts based upon the 'trimmed average' of all the 15 models. Then, we have also reported relative RMSE pertaining to inflation forecasts based upon the 'upper trimmed average' and 'lower trimmed average' of all the 15 models[36] in rows (xix) and (xx) respectively.

If we look at the results in rows (ii) to (xvii) of tables 2(a) to 2(c) we note the following. In most of the states and for majority of the inflation forecasting horizons simple average of forecasts works best for forecasting inflation in Pakistan except for high inflation state. In case of high inflation regime ARDL type modeling works best to forecast inflation in a developing country like Pakistan. If any approach other than simple averaging or ARDL turns out to be the best one, it is monetary indicators based VAR or Bayesian VAR model. But such are only 3 out of 24 cases (8 reported cases of inflation forecast horizons and there are 3 states – low, high and moderate). When we experimented to see if trimming helps improving the averaging forecast's performance, we find the answer in affirmative. We reported results; by including a row (numbered xviii) pertaining to 25 percent (from each sides) trimmed means of forecasts from all the 15 inflation forecasting models used in this study. However, we were surprised to see neither the simple average nor the trimmed average was useful in forecasting inflation in Pakistan during the high inflation regime in the country. We thought if one sided trimming is going to useful in extreme regimes. To see this we introduce two more rows (xix, and xx), containing relative RMSE pertaining to inflation forecasts based upon the 'upper (25 percent) trimmed average' and 'lower (25 percent) trimmed average' of all the 15 models. We do not see here any of the multiple equation VAR type model to perform better, for forecasting inflation in Pakistan, than the ARDL and various forms of averaging. In the following we discuss results reported in Tables 2(a) to 2(c) in some detail.

When relative RMSE is unity, it means the performance of inflation forecast model being compared is as good as that of RW model. In case it is greater (less) than unity, it means RW model performs better (poorer) than the model being compared. In each of the columns containing relative RMSE in Tables 2(a) to 2(c), the minimum relative RMSE is shown as a bold number to highlight which approach is the best for forecasting inflation in Pakistan at different horizons relative to the RW model.

[36] Similar results are also presented in tables 3.3 (a) through 3.3(c) of the appendix where we have provided RMSE relative to ARIMA as benchmark. Tables 4.3 (a) through 4.3(c) of the appendix contain RMSE relative to AR(1) as benchmark.

Now, if we look in the tables 2(a) to 2(c) we find that almost all the (classical) VAR models in almost all the states/horizons perform poorer than the random walk model for forecasting inflation in Pakistan. As discussed in the literature, performance of Bayesian VAR models in better compared to their (classical) VAR models for all the three states of inflation – low, high and moderate – in Pakistan. Some of the Bayesian VAR models (like BMVAR and BCMVAR) perform better than RW model but only in case of low and moderate inflation regimes. In case of moderate inflation regime in Pakistan even Bayesian VARs models fail to beat to the RW model in inflation forecasting at different horizons (except for a couple of cases of longer term horizons). ARDL modeling beats Bayesian VAR models, however, in most of the cases.

Simple averaging of forecasts leaves little room for any of the multiple equations modeling to for perform best. Once we use trimmed mean approach we find expect for high inflation regime, only one or other form of averaging is the best way to forecast inflation in developing countries like Pakistan. Upper trimmed averaging (for shorter horizons i.e. up to 6 months a head) and ARDL modeling (for longer horizons) provide best forecasts compared to the benchmark (RW) model for forecasting inflation in Pakistan during the low inflation environment. In case of moderate inflation, different ways to average the inflation forecasts work best to forecasts inflation in Pakistan. Simple 'averaging' and even the 'lower trimmed averaging' all the models' forecasts could not turn to be the best way to forecast inflation in a developing country like Pakistan during the high inflation regime. A (structural) ARDL modeling approach does the best job of forecasting inflation in Pakistan during the high inflation regime in the country. The reason could be simple: the ARDL modeling includes economic theory guided choice of predictors in the context of single equation models. Economic theory might help fight against the structural instabilities which are the biggest enemy of forecasting (Clements and Hendry, 1998, Giacomini, 2014). This type of modeling needs no theoretical restrictions (which are used in SVAR modeling), like in reduced form models which can potentially affect their forecast accuracy. Czudaj (2011) also found that though the Phillips curve forecasts outperform simple AR forecasts of Euro area rate of inflation but ARDL forecasting model improves upon the Phillips curve forecasts.

Similar results are also presented in tables 3(a) through 3(c) of the appendix where we have provided RMSE relative to ARIMA as benchmark. Tables 4 (a) through 4(c) of the appendix contain RMSE relative to AR(1) as benchmark. Choice of benchmark does not change main results of our study as we discussed above with reference to RW model as (best) benchmark model.

5. Conclusion

This paper primarily is an attempt to evaluate the models, from a suit of competing models, to see which can perform better than some benchmark model for generating judgment free point forecasts of inflation at different horizons for the case of Pakistan, where inflation is volatile being a developing country. We have been able to establish that some approaches to forecast inflation in Pakistan are better than the benchmark model (and competing models) for different forecast horizons and across different regimes of low, high and moderate inflation. However, there is no single approach which outperforms all others across all states and for all forecast horizons used in this study to produce point forecast of inflation in Pakistan.

Inflation forecasting models' performance is state dependent at least in the case of Pakistan. An ARDL type of modeling consisting of variables like changes in oil prices, exchange rate dynamics, real economic activity behaviour, and monetary growth turned out to be the best model for Pakistan for predicting inflation, for all horizons considered in this study, when it is going to be on higher side (like during December 2007 to June 2009). In high inflation environment in Pakistan even 'the lower trimmed average of the point forecasts from different competing models' produces poorer forecasts compared to (structural) ARDL modeling. In moderate inflation environment averaging inflation forecasts, from different models, beat all type of models' forecasts for all the forecasting horizons. When inflation is low, Upper trimmed averaging (for up to 6 months a head) and ARDL modeling (for longer horizons) is the best way to forecast inflation in Pakistan.

References:

Abbas, H., S. Beg, and M.A. Choudhary (2015), "Inflation Expectations and Economic Perceptions in a Developing Country Setting," *dsqx.sbp.org.pk/ccs/survey%20information/paper.pdf*

Adebiyi, A, A. Adewumi, A, O. and Ayo, C, K (2014), "Comparison of ARIMA and Artificial Neural Networks Models for Stock Price prediction", Journal of Applied Mathematics

Agha et al (2005), "Transmission Mechanism of Monetary Policy in Pakistan", SBP Research Bulletin, 1, 1.

Akdogan, K., Baser, S., Chadwick, M.G., Erutug, D., Hulagu, T. Kosem, S., Ogunc, F., Ozmen, M.U., and Tekatli, N. (2012), "Short term Inflation Forecasting Models for Turkey and a Forecast Combination Analysis," Turkiye Cumhuriyet Merkez Bankasi Working Paper No. 12/09.

Akaike, H. (1974), "A new look at the statistical model identification", IEEE Transactions on Automatic Control, 19. 6, 716–723,

Ali, Amjad (2014), "Share of imported goods in consumption of Pakistan," SBP Research Bulletin, Vol. 10 No. 1

Antipin. J, Boumidiene. F. J and Osterholm. P (2014), "Forecasting Inflation Using Constant Gain Least Squares", Australian Economic Papers, Flinders University, University of Adelaide and Wiley Publishing.

Atkeson, A. and L. Ohanian (2001), "Are Philips Curves useful for Forecasting Inflation?," Federal Reserve Bank of Minneapolis Quarterly Review, 25 (1)

Almounsor, A. (2010), "Inflation Dynamics in Yemen: An Empirical Analysis," IMF working paper No. 144

Bai. J, Perron. P (2003), "Computation and Analysis of Multiple Structural Change Models" Journal of Applied Econometrics, 18, 1-22

Benkovskis. K (2008), "Short-Term Forecasts of Latvia's Real Gross Domestic Product Growth Using Monthly Indicators", Working paper of Latvijas Banka, ISBN 9984-676-40-4

Bernanke et al (1997), "Systematic Monetary Policy and the Effects of Oil Price Shocks," Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution, vol. 28(1), 91-157.

Bilquees (1988), "Inflation in Pakistan: Empirical Evidence on the Monetarist and Structuralist Hypothesis", PDR, 2.

Bokil. M and Schimmelpfennig. A (2006), "Three Attempts at Inflation Forecasting in Pakistan", The Pakistan Development Review, 45, 3, 341-368

Bukhari, S. A.H.A.S, and S.U. Khan (2008), "Estimating Output Gap for Pakistan Economy: Structural and Statistical Approaches," SBP Research Bulletin, 4, 1

Bukhari. S. M. H and Feridun. M (2006), “Forecasting Inflation through Econometric Models: An Empirical study of Pakistani Data”, Doğuş Üniversitesi Dergisi, 7, 1, 39-47

Canova. F (2007), “G-7 Inflation Forecasts: Random walk, Philips Curve or What Else?,” Macroeconomic Dynamics, 11, pp: 1-30

Choudhary, M.A., A. Ali, S. Hussain, and V.J. Gabriel (2012), “Bank Lending and Monetary Shocks: Evidence from a Developing Economy,” SBP Working Paper 45.

Choudhary, M. A., S. Naeem, A. Faheem, N. Hanif, and F. Pasha (2011), “Formal Sector Price Discoveries, Preliminary Results from a Developing Country,” SBP Working Paper No. 42 and Discussion Paper No. 10, Department of Economics, University of Surrey, UK.

Choudhary, M.A. Sajawal Khan, Nadim Hanif, and Muhammad Rehman (2012), Procyclical Monetary Policy and Governance, SBP Research Bulletin, Vol. 8 No. 1

Clark, T.E. and M.W. McCracken (2011), “Advances in Forecast Evaluation,” FRB St. Louis Working Paper No. 025B.

Claus, E. and Claus, I. (2002), “How many jobs? A leading indicator model of New Zealand employment,” New Zealand Treasury Working Paper 02/13

Clements, M. P. and D.F. Hendry (2001), "Forecasting With Difference-Stationary and Trend-Stationary Models," Econometrics Journal, Royal Economic Society, Volume 4 No. 1, pp: S1-S19.

Czudaj, Robert (2011), “Improving Phillips Curve Based Inflation Forecasts: A Monetary Approach for the Euro Area,” Banks and Bank Systems, Volume 6, Issue 2, pp 5-14.

Diebold, F.X. and J.A. Lopez (1996), “Forecast Evaluation and Combination,” in G.S. Maddala and C.R. Rao (eds.), Handbook of Statistics, Amsterdam: North Holland.

Doan. T, Litterman. R. B and Sims. C.A (1983), “Forecasting and Conditional Projection Using Realistic Prior Distributions” NBER Working Paper No. 1202.

Elliott. G and Timmermann. A (2008), "Economic Forecasting," Journal of Economic Literature, American Economic Association, vol. 46(1), 3-56

Faust, J. and Wright, J, H. (2013) “Forecasting Inflation”, A chapter in the book “Economic Forecasting” Vol. 2A, Elsevier.

Giacomini, Raffaella (2014), “Economic Theory and Forecasting: The Lessons from Literature,” The Econometric Journal, (Accepted Article: http://onlinelibrary.wiley.com/doi/10.1111/ectj.12038/pdf).

Haider. A and Hanif. M. N (2009), “Inflation Forecasting in Pakistan using Artificial Neural Networks”, Pakistan Economic and Social Review, 47, 1, 123-138

Hamilton, J. D and Herrera, A. M. (2004), "Oil Shocks and Aggregate Macroeconomic Behavior: The Role of Monetary Policy: Comment," Journal of Money, Credit and Banking, Blackwell Publishing, Volume 36, No. 2, pp: 265-86.

Hanif, M. N. and I. Batool (2006), "Openness and Inflation: A Case Study of Pakistan," Pakistan Business Review, Karachi, Vol. 7 No. 4

Hanif, M.N., Malik, M.J. and Iqbal, J. (2012), "Intrinsic Inflation Persistence in Pakistan, SBP Working Paper No. 52.

Hanif, M. Nadim (2012), "A note on Food Inflation in Pakistan," Pakistan Economic and Social Review, Volume 50, No. 2, pp: 183-206

Hendry, D. F. and M. P. Clements (2003), "Economic Forecasting: Some Lessons From Recent Research," Economic Modelling, Elsevier, Volume 20 No. 2, pp: 301-329.

Hodrick, R. J. and Prescott, E. C. (1997), Postwar U.S. Business Cycles: An Empirical Investigation," Journal of Money, Credit and Banking, **29**, 1-16.

Irfan. M (2010), "A review of the Labour Market Research at PIDE 1957-2009", History of PIDE series-5

Khan. M. S and Schimmelpfennig. A (2006), "Inflation in Pakistan", PDR, 45:2, 185:202

Konstantins Benkovskis, 2008. "Short-Term Forecasts of Latvia's Real Gross Domestic Product Growth Using Monthly Indicators," Working Papers 2008/05, Latvijas Banka.

Montes, G, C. and Machado, C, C. (2013), "Credibility and Credit Channel Transmission of Monetary Policy Theoretical Model and Econometric Analysis", Journal of Economic Studies, 40, 4, 469-492.

Khan, Mahmood ul Hassan, and M. Nadim Hanif (2012) "Role of Demand and Supply Shocks in Driving Inflation: A Case Study of Pakistan," Journal of Independent Studies and Research, 10, 2

Meyer, Brent and Guhan Venkatu (2014), "Trimmed Mean Inflation Statistics: Just Hit the One in the Middle," FRB Atlanta Working Paper Number 2014-3.

Narayan, J. and Cicarelli, J. (1982), "A Note on the Informational Contents of Alternative Forecasting Benchmarks," Eastern Economic Journal, 8(4)

Nasim, Anjum (1997), "Determinants of inflation in Pakistan," State Bank of Pakistan

Norman, D. and A. Richards (2012), "Forecasting Performance of Single Equation Models of Inflation," The Economic Record, 88 (280) pp: 64-78

Qayyum, A., S. Khan and I. Khawaja (2005), "Interest rate Pass through in Pakistan: Evidence from a Transfer function Approach," Pakistan Development Review, 44 (4), Part II, pp: 975-1001

Riaz. M (2012), “Forecast Analysis of Food Price Inflation in Pakistan: Applying Rationality Criterion for VAR Forecast” Developing Country Studies, 2, 1

Riazuddin (2008), “An Exploratory Analysis of Inflation Episodes in Pakistan,” The Lahore Journal of Economics, (September), pp 63-93.

Robertson, John C. (2000), “Central Bank Forecasting: An International Comparison,” Federal Reserve Bank of Atlanta Economic Review, Second Quarter, pp: 21-32.

Sims. C. A (1980),"Macroeconomics and Reality", Econometrica, January 1980, 1-48.

Sims. C. A (1992), “Interpreting the Macroeconomic Time series Facts: The Effects of Monetary Policy”, European Economic Review, 36, 975-1011

Stock, J.H. and M.W. Watson (2004), “Combination Forecasts of Output Growth in Seven Country Data Set,” Journal of Forecasting, 23, 405-430.

Stock. J. H and Watson. M. W (2008) "Phillips curve inflation forecasts," Conference Series ; [Proceedings], Federal Reserve Bank of Boston, vol. 53.

Svensson. L. E. O (2005), "Monetary Policy with Judgment: Forecast Targeting," International Journal of Central Banking, International Journal of Central Banking, vol. 1(1), May.

Zeileis A., Kleiber, C. and Kramer, W. (2003), “Testing and Dating of Structural Changes in Practice”, Computational Statistics and Data Analysis, 44, 109-123

Appendix:

Models used in this study

a) ARIMA Model - The Benchmark Model

An ARIMA model is finalized based upon Akaike Information Criterion (AIC); after selecting the order of differencing for both seasonal and non seasonal unit root. Since we have used monthly data frequency, the estimated ARIMA model is allowed to include seasonal AR and MA terms.

$$Y_t = \alpha + \sum_{i=1}^{n} \beta_i Y_{t-i} + \sum_{j=1}^{m} \gamma_j \in_{t-j} + SAR(k) + SMA(q) + \in_t$$

Where "n" is the order of AR terms and "m" is the order of MA terms, SAR and SMA are the seasonal AR and MA terms of order k and q respectively.

b) Single Equation Model - 1 (ARDL1)

$$GCPI_t = c_1 + \alpha_i \sum_{i=1}^{13} WALR_{t-i} + \beta_j \sum_{j=1}^{13} GOLP_{t-j} + \gamma_k \sum_{k=1}^{24} GIM2_{t-k} + \delta_l \sum_{l=1}^{13} GAP_{t-l} + \sum_{m=1}^{13} \theta_j GCPI_{t-m} + \in_{1t}$$

c) Single Equation Model - 2 (ARDL2)

$$GCPI_t = c_1 + \rho_i \sum_{i=1}^{13} WINF_{t-i} + \mu \sum_{j=1}^{13} CNER_{t-j} + \tau_k \sum_{k=1}^{24} GIM2_{t-k} + \varphi_l \sum_{l=1}^{13} CLSM_{t-l} + \sum_{m=1}^{13} \omega_j GCPI_{t-m} + \in_{2t}$$

d) MVAR1 Model

This (monetary) structural VAR is specified as[37]

$$DISR_t = E_{t-1}DISR_t + \in_t^{DISR}$$

$$WALR_t = E_{t-1}WALR_t + \lambda 1 \in_t^{DISR} + \in_t^{WALR}$$

$$GIM0_t = E_{t-1}GIM0_t + \lambda 2 \in_t^{DISR} + \lambda 3 \in_t^{WALR} + \in_t^{GIM0}$$

$$GIM2_t = E_{t-1}GIM2_t + \lambda 4 \in_t^{DISR} + \lambda 5 \in_t^{WALR} + \lambda 6 \in_t^{GIM0} + \in_t^{GIM2}$$

$$GCPI_t = E_{t-1}GICP_t + \lambda 7 \in_t^{DISR} + \lambda 8 \in_t^{WALR} + \lambda 9 \in_t^{GIM0} + \lambda 10 \in_t^{GIM2} + \in_t^{GCPI}$$

[37] E_{t-1} here in these models is the conditional expectation operator and $\lambda's$ are the impulse response coefficients.

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where $Y = (DISR, WALR, GIM0, GIM2, GCPI)$, $\in = (\in^{DISR}, \in^{WALR}, \in^{GIM0}, \in^{GIM2}, \in^{GCPI})$ and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 \end{bmatrix}$$

e) MVAR2 Model

This (monetary) structural VAR2 is specified as[38]

$DISR_t = E_{t-1}DISR_t + \in_t^{DISR}$

$GIM0_t = E_{t-1}GIM0_t + \lambda 1 \in_t^{DISR} + \in_t^{GIM0}$

$GIM2_t = E_{t-1}GIM2_t + \lambda 2 \in_t^{DISR} + \lambda 3 \in_t^{GIM0} + \in_t^{GIM2}$

$GAP_t = E_{t-1}GAP_t + \lambda 4 \in_t^{DISR} + \lambda 5 \in_t^{GIM0} + \lambda 6 \in_t^{GIM2} + \in_t^{GAP}$

$GCPI_t = E_{t-1}GICP_t + \lambda 7 \in_t^{DISR} + \lambda 8 \in_t^{GIM0} + \lambda 9 \in_t^{GIM2} + \lambda 10 \in_t^{GAP} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where $Y = (DISR, GIM0, GIM2, GAP, GCPI)$, $\in = (\in^{DISR}, \in^{GIM0}, \in^{GIM2}, \in^{GAP}, \in^{GCPI})$ and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 \end{bmatrix}$$

f) CVAR1 Model

This (credit) structural VAR is specified as

$DISR_t = E_{t-1}Disr_t + \in_t^{DISR}$

[38] E_{t-1} here in these models is the conditional expectation operator and $\lambda's$ are the impulse response coefficients.

$TBLR_t = E_{t-1}TBLR_t + \lambda 1 \in_t^{DISR} + \in_t^{TBLR}$

$GPSB_t = E_{t-1}GPBS_t + \lambda 2 \in_t^{DISR} + \lambda 3 \in_t^{TBLR} + \in_t^{GPSB}$

$WALR_t = E_{t-1}WALR_t + \lambda 4 \in_t^{DISR} + \lambda 5 \in_t^{TBLR} + \lambda 6 \in_t^{GPSB} + \in_t^{WALR}$

$GPSC_t = E_{t-1}GPSC_t + \lambda 7 \in_t^{DISR} + \lambda 8 \in_t^{TBLR} + \lambda 9 \in_t^{GPSB} + \lambda 10 \in_t^{WALR} + \in_t^{GPSC}$

$GCPI_t = E_{t-1}GCPI_t + \lambda 11 \in_t^{DISR} + \lambda 12 \in_t^{TBLR} + \lambda 13 \in_t^{GPSB} + \lambda 14 \in_t^{WALR} + \lambda 15 \in_t^{GPSC} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where $Y = (DISR, TBLR, GPSB, WALR, GPSC, GCPI)$,

$\in = (\in^{DISR}, \in^{TBLR}, \in^{GPSB}, \in^{WALR}, \in^{GPSC}, \in^{GCPI})$and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{15} & 1 \end{bmatrix}$$

g) CVAR2 Model

This (credit) structural VAR is specified as

$DISR_t = E_{t-1}Disr_t + \in_t^{DISR}$

$TBLR_t = E_{t-1}TBLR_t + \lambda 1 \in_t^{DISR} + \in_t^{TBLR}$

$GPSB_t = E_{t-1}GPBS_t + \lambda 2 \in_t^{DISR} + \lambda 3 \in_t^{TBLR} + \in_t^{GPSB}$

$WALR_t = E_{t-1}WALR_t + \lambda 4 \in_t^{DISR} + \lambda 5 \in_t^{TBLR} + \lambda 6 \in_t^{GPSB} + \in_t^{WALR}$

$GPSC_t = E_{t-1}GPSC_t + \lambda 7 \in_t^{DISR} + \lambda 8 \in_t^{TBLR} + \lambda 9 \in_t^{GPSB} + \lambda 10 \in_t^{WALR} + \in_t^{GPSC}$

$CLSM_t = E_{t-1}CPLSM_t + \lambda 11 \in_t^{DISR} + \lambda 12 \in_t^{TBLR} + \lambda 13 \in_t^{GPSB} + \lambda 14 \in_t^{WALR} + \lambda 15 \in_t^{GPSC} + \in_t^{CLSM}$

$$GCPI_t = E_{t-1}GCPI_t + \lambda 16 \in_t^{DISR} + \lambda 17 \in_t^{TBLR} + \lambda 18 \in_t^{GPSB} + \lambda 19 \in_t^{WALR} + \lambda 20 \in_t^{GPSC} + \lambda 21 \in_t^{CLSM} + \in_t^{GCPI}$$

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where

$Y = (DISR, TBLR, GPSB, WALR, GPSC, CLSM, GCPI)$,
$\in = (\in^{DISR}, \in^{TBLR}, \in^{GPSB}, \in^{WALR}, \in^{GPSC}, \in^{CLSM}, \in^{GCPI})$,

and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{115} & 1 & 0 \\ \lambda_{16} & \lambda_{17} & \lambda_{18} & \lambda_{19} & \lambda_{20} & \lambda_{21} & 1 \end{bmatrix}$$

h) CVAR3 Model

This (credit) structural VAR is specified as

$DISR_t = E_{t-1} Disr_t + \in_t^{DISR}$

$GPSB_t = E_{t-1} GPSB_t + \lambda 1 \in_t^{DISR} + \in_t^{GPSB}$

$WALR_t = E_{t-1} WALR_t + \lambda 2 \in_t^{DISR} + \lambda 3 \in_t^{GPSB} + \in_t^{WALR}$

$GPSC_t = E_{t-1} GPSC_t + \lambda 4 \in_t^{DISR} + \lambda 5 \in_t^{GPSB} + \lambda 6 \in_t^{WALR} + \in_t^{GPSC}$

$CLSM_t = E_{t-1} CLSM_t + \lambda 7 \in_t^{DISR} + \lambda 8 \in_t^{GPSB} + \lambda 9 \in_t^{WALR} + \lambda 10 \in_t^{GPSC} + \in_t^{CLSM}$

$GCPI_t = E_{t-1} GCPI_t + \lambda 11 \in_t^{DISR} + \lambda 12 \in_t^{GPSB} + \lambda 13 \in_t^{WALR} + \lambda 14 \in_t^{GPSC} + \lambda 15 \in_t^{CLSM} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where $Y = (DISR, GPSB, WALR, GPSC, CLSM, GCPI)$,

$\in = (\in^{DISR}, \in^{GPSB}, \in^{WALR}, \in^{GPSC}, \in^{CLSM}, \in^{GCPI})$,

and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{15} & 1 \end{bmatrix}$$

i) EVAR1 Model

This (external) structural VAR is specified as

$GOLP_t = E_{t-1}GOLP_t + \in_t^{GOLP}$

$GFIP_t = E_{t-1}GFIP_t + \lambda 1 \in_t^{GOLP} + \in_t^{GFIP}$

$GWRM_t = E_{t-1}GWRM_t + \lambda 2 \in_t^{GOLP} + \lambda 3 \in_t^{GFIP} + \in_t^{GWRM}$

$CRER_t = E_{t-1}CRER_t + \lambda 4 \in_t^{GOLP} + \lambda 5 \in_t^{GFIP} + \lambda 6 \in_t^{GWRM} + \in_t^{CRER}$

$CLSM_t = E_{t-1}CPLSM_t + \lambda 7 \in_t^{GOLP} + \lambda 8 \in_t^{GFIP} + \lambda 9 \in_t^{GWRM} + \lambda 10 \in_t^{CRER} + \in_t^{CLSM}$

$GCPI_t = E_{t-1}GCPI_t + \lambda 11 \in_t^{GOLP} + \lambda 12 \in_t^{GFIP} + \lambda 13 \in_t^{GWRM} + \lambda 14 \in_t^{CRER} + \lambda 15 \in_t^{CLSM} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system

$Y_T = AY_{T-1} + B \in_t$, Where

$Y = (GOLP, GFIP, GWRM, CRER, CLSM, GCPI)$, $\in = (\in^{GOLP}, \in^{GFIP}, \in^{GWRM}, \in^{CRER}, \in^{CLSM}, \in^{GCPI})$ and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{15} & 1 \end{bmatrix}$$

j) EVAR2 Model

This (external) structural VAR is specified as:

$WCPC_t = E_{t-1}WCPC_t + \in_t^{WCPC}$

$CNER_t = E_{t-1}CNER_t + \lambda 1 \in_t^{WCPC} + \lambda 2 \in_t^{GCPI} + \in_t^{CNER}$

$GIM2_t = E_{t-1}GIM2_t + \lambda 3 \in_t^{WCPC} + \lambda 4 \in_t^{CNER} + \in_t^{GIM2}$

$GLSM_t = E_{t-1}GLSM_t + \lambda 5 \in_t^{WCPC} + \lambda 6 \in_t^{CNER} + \lambda 7 \in_t^{GIM2} + \in_t^{GLSM}$

$GCPI_t = E_{t-1}GCPI_t + \lambda 8 \in_t^{WCPC} + \lambda 9 \in_t^{GLSM} + \lambda 10 \in_t^{GIM2} + \lambda 11 \in_t^{CNER} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system:

$Y_T = AY_{T-1} + B \in_t$

Where $Y = (WCPC, CNER, GIM2, GLSM, GCPI)$ and $\in = (\in^{WCPC}, \in^{CNER}, \in^{GIM2}, \in^{GLSM}, \in^{GCPI})$ and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & \lambda_2 \\ \lambda_3 & \lambda_4 & 1 & 0 & 0 \\ \lambda_5 & \lambda_6 & \lambda_7 & 1 & 0 \\ \lambda_8 & \lambda_9 & \lambda_{10} & \lambda_{11} & 1 \end{bmatrix}$$

k) EVAR3 Model

This (external) structural VAR is specified as

$GOLP_t = E_{t-1}GOLP_t + \in_t^{GOLP}$

$GFIP_t = E_{t-1}GFIP_t + \lambda 1 \in_t^{GOLP} + \in_t^{GFIP}$

$DISR_t = E_{t-1}DISR_t + \lambda 2 \in_t^{GOLP} + \lambda 3 \in_t^{GFIP} + \in_t^{DISR}$

$CRER_t = E_{t-1}CRER_t + \lambda 4 \in_t^{GOLP} + \lambda 5 \in_t^{GFIP} + \lambda 6 \in_t^{DISR} + \in_t^{CRER}$

$GWRM_t = E_{t-1}GWRM_t + \lambda 7 \in_t^{GOLP} + \lambda 8 \in_t^{GFIP} + \lambda 9 \in_t^{DISR} + \lambda 10 \in_t^{CRER} + \in_t^{GWRM}$

$CLSM_t = E_{t-1}CLSM_t + \lambda 11 \in_t^{GOLP} + \lambda 12 \in_t^{GFIP} + \lambda 13 \in_t^{DISR} + \lambda 14 \in_t^{CRER} + \lambda 15 \in_t^{GWRM} + \in_t^{CLSM}$

$GCPI_t = E_{t-1}GCPI_t + \lambda 16 \in_t^{GOLP} + \lambda 17 \in_t^{GFIP} + \lambda 18 \in_t^{DISR} + \lambda 19 \in_t^{CRER} + \lambda 20 \in_t^{GWRM} + \lambda 21 \in_t^{CLSM} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system

$Y_T = AY_{T-1} + B \in_t$, Where

Where; $Y = (GOLP, GFIP, DISR, CRER, GWRM, CLSM, GCPI)$, $\in = (\in^{GOLP}, \in^{GFIP}, \in^{DISR}, \in^{CRER}, \in^{GWRM}, \in^{CLSM}, \in^{GCPI})$ and

and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{115} & 1 & 0 \\ \lambda_{16} & \lambda_{17} & \lambda_{18} & \lambda_{19} & \lambda_{20} & \lambda_{21} & 1 \end{bmatrix}$$

l) CMVAR Model

This (comprehensive) structural VAR is specified as:

$GOLP_t = E_{t-1}GOLP_t + \in_t^{GOLP}$

$CRER_t = E_{t-1}CRER_t + \lambda 1 \in_t^{GOLP} + \in_t^{CRER}$

$DISR_t = E_{t-1}DISR_t + \lambda 2 \in_t^{GOLP} + \lambda 3 \in_t^{CRER} + \in_t^{DISR}$

$GIM2_t = E_{t-1}GIM2_t + \lambda 4 \in_t^{GOLP} + \lambda 5 \in_t^{CRER} + \lambda 6 \in_t^{DISR} + \in_t^{GIM2}$

$CLSM_t = E_{t-1}CLSM_t + \lambda 7 \in_t^{GOLP} + \lambda 8 \in_t^{CRER} + \lambda 9 \in_t^{DISR} + \lambda 10 \in_t^{GIM2} + \in_t^{CLSM}$

$GCPI_t = E_{t-1}GCPI_t + \lambda 11 \in_t^{GOLP} + \lambda 12 \in_t^{CRER} + \lambda 13 \in_t^{DISR} + \lambda 14 \in_t^{CIM2} + +\lambda 15 \in_t^{CLSM} + \in_t^{GCPI}$

It gives us the following recursive structural VAR system

$Y_T = AY_{T-1} + B \in_t$, Where

Where,

$Y = (GOLP, CRER, DISR, CIM2, CLSM, GCPI)$,

$\in = (\in^{GOLP}, \in^{CRER}, \in^{DISR}, \in^{CIM2}, \in^{CLSM}, \in^{GCPI})$

and

$$B = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ \lambda_1 & 1 & 0 & 0 & 0 & 0 \\ \lambda_2 & \lambda_3 & 1 & 0 & 0 & 0 \\ \lambda_4 & \lambda_5 & \lambda_6 & 1 & 0 & 0 \\ \lambda_7 & \lambda_8 & \lambda_9 & \lambda_{10} & 1 & 0 \\ \lambda_{11} & \lambda_{12} & \lambda_{13} & \lambda_{14} & \lambda_{15} & 1 \end{bmatrix}$$

Table 1 (a) : Selected Literature on Inflation Forecast Evaluation-Developing Countries

Study	**Country/Frequency/ Sample/Variable of interest**	**Model and other Variables**	**Findings**	**Forecast Evaluation: Benchmark Criterion**
Riaz (2012)	Pakistan. Quarterly. 1975-2008. Food and general CPI inflation (YoY)	VAR Model. Real GDP, M2, Interest rate and Exchange rate	Food Inflation forecasts are found to be efficient and fulfill the criteria of weak and strong rationality. This conclusion does not hold for General Inflation.	No Benchmark Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil's Inequality Coefficient (TIC)
Haider and Hanif (2009)	Pakistan. Monthly Data for General YOY inflation From July 1993 to June 2007	AR (1), ARIMA and ANN	ANN is found to be better than AR (1) and ARIMA based on RMSE for 12 month forecasts.	ARIMA Benchmark RMSE
Bokil and Schimmelpfennig (2006)	Pakistan. Monthly Data for July 1998 to December 2004 general 12 month average inflation	Leading Indicator Model (LIM), VAR Model and ARIMA model. Broad Money, Reserve Money, Credit to Private Sector, Six Months Treasury Bills Rate Large Scale Manufacturing Index and Output Gap.	LIM is considered to be the best model for the forecast of six months July 2004 to Dec 2004. The LIM model containing broad money growth, private sector credit growth and lags of inflation has the minimum RMSE.	No Benchmark. RMSE
Bukhari and Feridun (2006)	Pakistan. Monthly Data 1991 to 2004 CPI inflation	ARIMA and VAR. CPI, WPI, M2 and Weighted Average Lending Rates	ARIMA model performs better than VAR according to relative MSE.	ARIMA Benchmark Relative RMSE

Table 1 (a) Selected Literature on Inflation Forecast Evaluation-Developed Countries

Study	Country/Frequency/ Sample/Variable of interest	Model and other Variables	Findings	Forecast Evaluation: Benchmark Criterion
Atkeson and Ohanian (2001)	USA Quarterly 1965 Q4 to 1999Q4 CPI Core CPI PCE Deflator	NAIRU Philips Curve	15 Year recursive forecast reveals that Philips Curve forecasts are better than naïve forecast	Benchmark used is Random Walk Model.
Norman and Richards (2012)	Australia Quarterly 1982Q1-2009Q4 CPI Inflation Trimmed Mean QoQ Inflation	Philips Curve, Mark-up Model, Distributed lag model and GPT Philips Curve VAR FAVAR	GPT Philips Curve model outperforms VAR and FAVAR forecasts.	Benchmark used is Random Walk Model.
Elliot and Timmermann (2008)	USA Monthly 1959:1 2003:12 CPI MoM Inflation	AR, BVAR, Exponential Smoothing, STAR and ANN	Simple Average forecast is the best and exponential smoothing is the second best for recursive forecasts.	No Benchmark. MSE of model using Giacomini and White (2006) approach.
Antipin et al (2014)	Australia, Sweden, UK and USA Quarterly 1970 Q1- 1985Q1 CPI QoQ Inflation	AR (p)	AR (p) model by constant gain least squares CGLS is better than OLS	Benchmark AR (p) Relative RMSE.
Stock and Watson (2008)	USA Quarterly 1953 Q1- 2008Q1 CPI, CPI core, PCE-all, PCE-core and GDP Deflator QoQ Inflation	157 distinct Models and 35 combination forecasts	Performance of Philips curve is episodic. For instance in late 90's its forecasts were better than AR (p) model. In mid 90's univariate benchmark models outperform other multivariate models.	Benchmark AR (p) and Random Walk model. Relative RMSE

Figure 1: Observed and Target/SBP Forecast of 12-month Average YoY Inflation

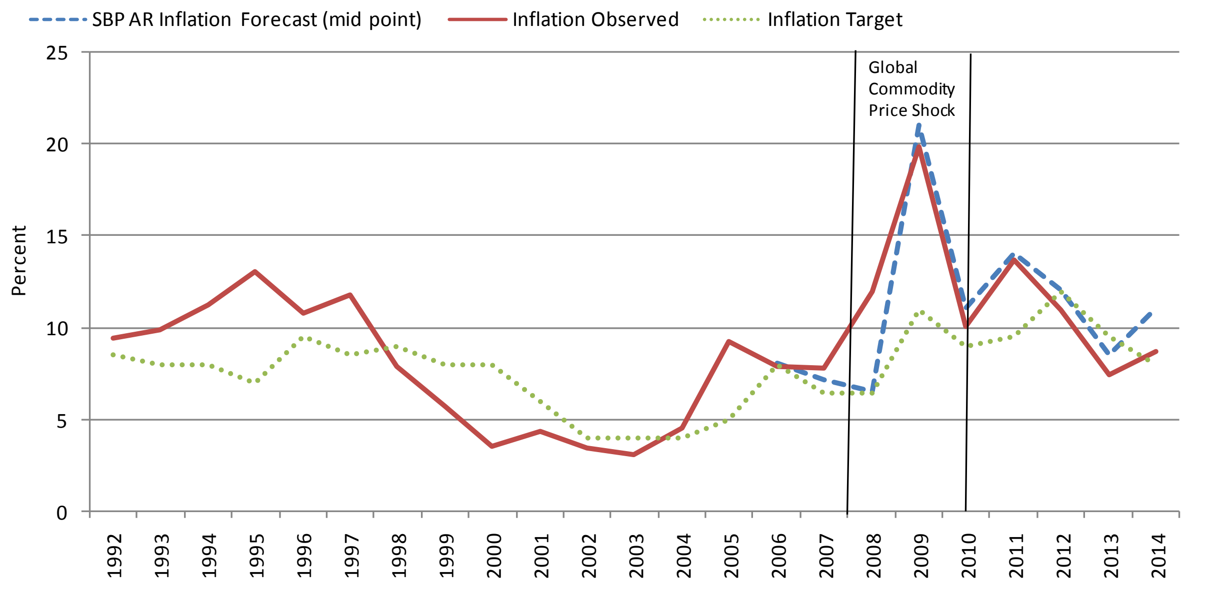
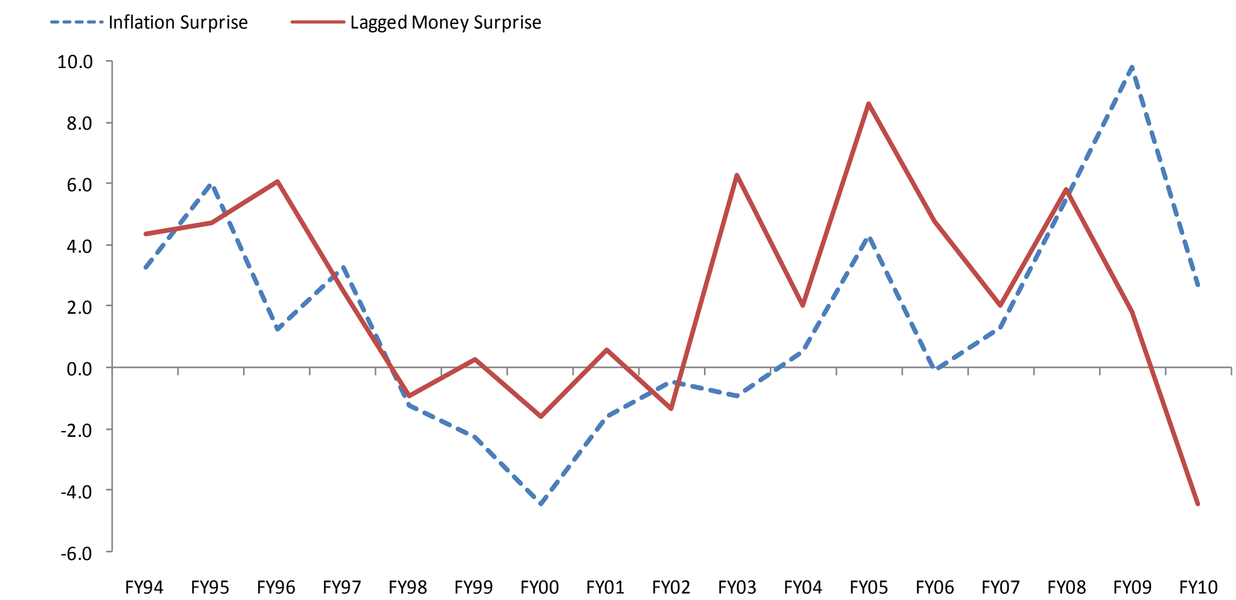
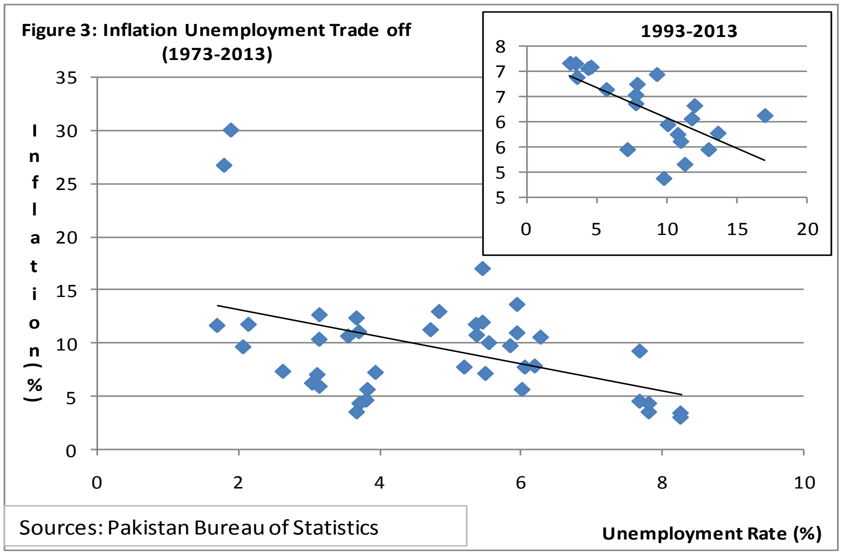


Fig: 2 Inflation and Money Surprise (%)





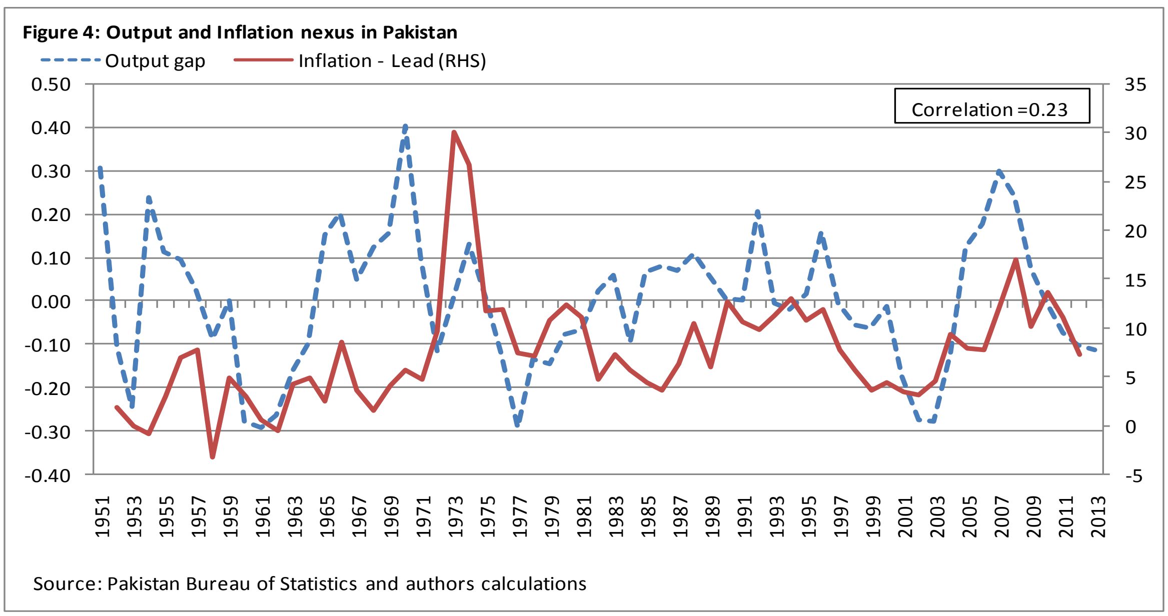


Table 1 (b) : Some Stylized Facts about Inflation in Pakistan

Period	Minimum	Average	Maximum	Dispersion	Regime
Jul 1958 to Jun 2014	-10.32	7.7	37.81	8.8	Overall inflation data availability[39]
Jul 1992 to Jun 2014	1.41	9.0	24.86	4.3	Estimation period of this study
Jul 2002 to Nov 2007	1.41	6.6	11.10	2.5	Low-inflation period
Dec 2007 to Jun 2009	8.79	18.0	24.86	5.2	High-inflation period
Jul 2009 to Jun 2014	5.13	10.2	15.45	2.5	Moderate-inflation period
Source: Pakistan Bureau of Statistics and authors' calculations					

[39] Consistent data for all the other variables used in this study is not readily available for this entire period. That is why our inflation forecast evaluation analysis is over the period of Jul 1992 to Jun 2014.

Table 1 (c): List of Variables

Variable	**Source**
Pakistan's overnight reverse repo rate (discount rate)	SBP*
(Weighted average) lending rate charged by commercial banks in Pakistan	SBP
Pakistan's reserve money (M0)	SBP
Pakistan's broad money (M2)	SBP
Pakistan's consumer price index (CPI)	PBS**
Global oil price (average of 3 spot crude oil prices - Brent, WTI# and Dubai Fathah)	IFS***
United States industrial production index	IFS
Remittances sent to Pakistan by Pakistanis working abroad	SBP
Real effective exchange rate (of Pak Rupee)	IFS
Nominal exchange rate (Pak Rupee per US$)	IFS
Pakistan's large scale manufacturing index	PBS
World commodities' price index	IFS
Cut-off rates of 6 months Treasury Bills (Government of Pakistan)	SBP
(Pakistan) Government borrowing from the banking system	SBP
Private sector credit disbursed by commercial banks in Pakistan	SBP
Pakistan's real GDP	PBS
Pakistan local oil (high speed diesel, petrol super and kerosene oil) prices' index	PBS
Pakistan's unemployment rate	PBS
#: West Texas Intermediate. *: State Bank of Pakistan. **: Pakistan Bureau of Statistics. ***: International Financial Statistics of International Monetary Fund.	

Table 1 (d): Zeileis (2003) Structural Change Test

No of Breaks	Date of Break	BIC
0		786.3
1	December 2007	725.2
2	December 2007 ,July 2009	675.0*
*: BIC attained its minimum while we searched for two breaks.		

Table: 2 (a) RMSE (Relative to RW model as benchmark) for Jul 2002 to Nov 2007 (Low Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	3.67	2.99	0.57	0.80	0.89	1.10	0.27	0.61
(iii)	ARDL2	2.95	4.53	**0.45**	**0.43**	**0.54**	1.06	**0.19**	**0.38**
(iv)	MVAR1	1.25	1.37	1.22	1.15	1.11	1.13	1.21	1.31
(v)	MVAR2	1.23	1.32	1.23	1.28	1.28	1.29	1.37	1.41
(vi)	CVAR1	1.50	1.92	1.91	2.08	2.31	2.61	3.12	4.04
(vii)	CVAR2	1.84	2.42	2.50	2.87	3.62	5.01	7.66	12.38
(viii)	CVAR3	1.97	2.45	2.58	3.03	3.88	5.31	7.92	12.29
(ix)	EVAR1	1.50	1.39	1.17	1.21	1.40	1.57	1.68	1.73
(x)	EVAR2	1.13	1.17	1.18	1.22	1.23	1.29	1.35	1.43
(xi)	EVAR3	1.60	1.71	1.41	1.65	2.28	3.39	5.29	8.18
(xii)	CMVAR	1.27	1.45	1.31	1.33	1.29	1.34	1.45	1.51
(xiii)	BMVAR	0.99	0.97	0.97	0.97	0.96	0.96	0.97	0.98
(xiv)	BEVAR	1.02	1.02	1.02	1.03	1.03	1.04	1.05	1.05
(xv)	BCVAR	1.03	1.04	1.04	1.07	1.08	1.11	1.15	1.17
(xvi)	BCMVAR	0.99	0.97	0.96	0.97	0.97	0.97	0.99	1.00
(xvii)	Simple Average	0.93	0.99	1.03	1.07	1.14	1.31	1.68	2.36
(xviii)	Trimmed Average	0.92	0.94	0.98	1.01	1.04	1.06	1.09	1.11
(xix)	U- Trimmed Average	**0.72**	**0.73**	0.75	0.73	0.74	**0.81**	0.78	0.81
(xx)	L- Trimmed Average	0.99	1.03	1.05	1.10	1.18	1.36	1.78	2.55
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 2 (b) RMSE (Relative to RW model as benchmark) for Dec 2007 to Jun 2009 (High Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	**0.47**	0.37	0.41	**0.44**	**0.22**	**0.30**	**0.46**	0.71
(iii)	ARDL2	0.47	**0.36**	**0.40**	0.69	0.24	0.37	0.51	**0.54**
(iv)	MVAR1	0.98	1.04	1.13	1.22	1.28	1.39	1.50	1.60
(v)	MVAR2	0.72	0.82	0.96	1.05	0.91	0.74	0.65	1.16
(vi)	CVAR1	1.10	1.17	1.31	1.50	1.73	2.05	2.47	2.94
(vii)	CVAR2	1.11	1.17	1.31	1.50	1.73	2.04	2.46	2.92
(viii)	CVAR3	1.12	1.18	1.33	1.53	1.78	2.12	2.59	3.12
(ix)	EVAR1	0.98	1.08	1.23	1.60	2.01	2.50	3.16	3.80
(x)	EVAR2	0.93	0.97	1.03	1.08	0.91	0.66	0.63	0.80
(xi)	EVAR3	1.05	1.12	1.24	1.54	1.79	2.05	2.32	2.52
(xii)	CMVAR	0.79	0.81	0.84	0.93	1.12	1.43	1.73	1.82
(xiii)	BMVAR	0.89	0.90	0.92	0.93	0.92	0.93	0.93	0.86
(xiv)	BEVAR	0.95	1.01	1.12	1.27	1.42	1.65	1.90	2.13
(xv)	BCVAR	0.95	1.01	1.10	1.21	1.33	1.50	1.70	1.87
(xvi)	BCMVAR	0.87	0.89	0.92	0.96	0.98	1.03	1.08	1.05
(xvii)	Simple Average	0.86	0.91	0.98	1.10	1.21	1.36	1.57	1.76
(xviii)	Trimmed Average	0.90	0.93	0.95	1.19	1.34	1.53	1.67	1.49
(xix)	U- Trimmed Average	0.77	0.74	0.60	0.73	0.88	0.97	1.06	0.76
(xx)	L- Trimmed Average	0.95	1.00	0.97	1.29	1.50	1.74	2.04	2.14
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 2 (c) RMSE (Relative to RW model as benchmark) for Jul 2009 to Jun 2014 (Moderate Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	1.40	1.66	2.53	3.12	0.65	1.14	1.43	2.14
(iii)	ARDL2	1.34	1.40	1.51	2.04	**0.60**	0.85	1.19	1.92
(iv)	MVAR1	1.16	1.29	1.26	1.15	1.13	0.99	0.79	0.63
(v)	MVAR2	1.30	1.62	1.58	1.40	1.30	1.10	0.92	0.79
(vi)	CVAR1	1.23	1.92	2.76	2.70	2.55	2.28	1.41	1.22
(vii)	CVAR2	1.01	1.08	1.13	1.12	1.11	1.03	0.90	0.81
(viii)	CVAR3	1.13	1.49	1.69	1.51	1.44	1.08	0.85	0.78
(ix)	EVAR1	1.93	2.75	3.41	3.38	2.93	2.25	1.13	0.75
(x)	EVAR2	1.22	1.50	1.51	1.28	1.12	1.19	1.35	1.42
(xi)	EVAR3	1.70	2.24	2.54	2.33	2.01	1.81	1.47	1.31
(xii)	CMVAR	1.53	1.90	1.99	1.87	1.57	1.23	0.90	0.68
(xiii)	BMVAR	1.11	1.24	1.28	1.20	1.21	1.14	1.01	0.86
(xiv)	BEVAR	1.02	1.10	1.09	1.05	1.10	1.05	0.93	0.85
(xv)	BCVAR	1.14	1.31	1.39	1.36	1.37	1.31	1.16	1.03
(xvi)	BCMVAR	1.03	1.10	1.07	1.02	1.06	1.00	0.90	0.77
(xvii)	Simple Average	**0.85**	0.95	0.85	**0.74**	0.71	0.66	**0.67**	0.67
(xviii)	Trimmed Average	0.88	1.02	0.82	0.83	0.87	0.81	0.69	**0.60**
(xix)	U- Trimmed Average	0.92	**0.94**	**0.82**	0.82	0.91	0.85	0.73	0.61
(xx)	L- Trimmed Average	0.94	1.41	1.03	0.96	0.67	**0.62**	0.71	0.66
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 3 (a) RMSE (Relative to ARIMA model as benchmark) for Jul 2002 to Nov 2007 (Low Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	3.65	3.00	0.57	0.79	0.89	1.10	0.27	0.60
(iii)	ARDL2	2.93	4.54	**0.45**	**0.43**	**0.54**	1.06	**0.19**	**0.38**
(iv)	MVAR1	1.24	1.38	1.22	1.15	1.11	1.12	1.21	1.31
(v)	MVAR2	1.22	1.32	1.23	1.28	1.27	1.29	1.36	1.40
(vi)	CVAR1	1.49	1.92	1.91	2.08	2.30	2.60	3.11	4.02
(vii)	CVAR2	1.83	2.42	2.50	2.86	3.61	5.00	7.64	12.33
(viii)	CVAR3	1.96	2.46	2.58	3.03	3.87	5.29	7.89	12.23
(ix)	EVAR1	1.49	1.40	1.17	1.21	1.39	1.56	1.68	1.72
(x)	EVAR2	1.13	1.18	1.18	1.22	1.23	1.29	1.35	1.42
(xi)	EVAR3	1.59	1.71	1.41	1.64	2.28	3.38	5.27	8.14
(xii)	CMVAR	1.26	1.45	1.31	1.33	1.29	1.34	1.44	1.51
(xiii)	BMVAR	0.98	0.97	0.97	0.97	0.96	0.96	0.97	0.98
(xiv)	BEVAR	1.01	1.02	1.02	1.02	1.03	1.04	1.05	1.05
(xv)	BCVAR	1.02	1.04	1.04	1.06	1.08	1.11	1.14	1.16
(xvi)	BCMVAR	0.99	0.97	0.96	0.97	0.97	0.97	0.99	1.00
(xvii)	Simple Average	0.92	0.99	1.03	1.07	1.14	1.30	1.68	2.35
(xviii)	Trimmed Average	0.91	0.94	0.97	1.01	1.04	1.06	1.09	1.10
(xix)	U- Trimmed Average	**0.71**	**0.73**	0.75	0.73	0.74	**0.81**	0.78	0.81
(xx)	L- Trimmed Average	0.98	1.03	1.05	1.09	1.18	1.36	1.77	2.54

Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.

Table: 3 (b) RMSE (Relative to ARIMA model as benchmark) for Dec 2007 to Jun 2009 (High Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	**0.45**	0.33	0.32	**0.30**	**0.13**	**0.15**	**0.19**	0.24
(iii)	ARDL2	0.46	**0.32**	**0.31**	0.47	0.14	0.18	0.21	**0.19**
(iv)	MVAR1	0.95	0.93	0.88	0.82	0.75	0.68	0.61	0.55
(v)	MVAR2	0.70	0.73	0.75	0.71	0.53	0.36	0.27	0.40
(vi)	CVAR1	1.06	1.04	1.03	1.02	1.01	1.01	1.01	1.01
(vii)	CVAR2	1.07	1.04	1.03	1.01	1.01	1.00	1.00	1.01
(viii)	CVAR3	1.08	1.05	1.04	1.04	1.04	1.04	1.06	1.07
(ix)	EVAR1	0.95	0.96	0.97	1.08	1.18	1.23	1.29	1.31
(x)	EVAR2	0.90	0.86	0.80	0.73	0.53	0.33	0.26	0.28
(xi)	EVAR3	1.02	0.99	0.97	1.04	1.04	1.01	0.95	0.87
(xii)	CMVAR	0.76	0.72	0.66	0.63	0.65	0.70	0.71	0.63
(xiii)	BMVAR	0.86	0.80	0.72	0.63	0.54	0.46	0.38	0.30
(xiv)	BEVAR	0.91	0.90	0.88	0.86	0.83	0.81	0.77	0.73
(xv)	BCVAR	0.92	0.90	0.86	0.82	0.78	0.74	0.69	0.64
(xvi)	BCMVAR	0.84	0.79	0.72	0.65	0.57	0.51	0.44	0.36
(xvii)	Simple Average	0.83	0.81	0.77	0.75	0.71	0.67	0.64	0.61
(xviii)	Trimmed Average	0.87	0.83	0.74	0.81	0.78	0.75	0.68	0.51
(xix)	U- Trimmed Average	0.74	0.66	0.47	0.50	0.51	0.48	0.43	0.26
(xx)	L- Trimmed Average	0.92	0.89	0.76	0.88	0.88	0.85	0.83	0.74

Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.

Table: 3 (c) RMSE (Relative to ARIMA model as benchmark) for Jul 2009 to Jun 2014 (Moderate Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	1.18	1.45	2.19	2.81	0.60	1.05	1.34	1.99
(iii)	ARDL2	1.13	1.23	1.30	1.84	**0.56**	0.78	1.12	1.79
(iv)	MVAR1	0.97	1.13	1.09	1.04	1.04	0.91	0.74	0.59
(v)	MVAR2	1.09	1.42	1.37	1.26	1.20	1.01	0.86	0.73
(vi)	CVAR1	1.04	1.68	2.39	2.44	2.36	2.08	1.32	1.14
(vii)	CVAR2	0.85	0.95	0.98	1.01	1.02	0.94	0.84	0.75
(viii)	CVAR3	0.95	1.31	1.46	1.37	1.33	0.99	0.80	0.72
(ix)	EVAR1	1.63	2.41	2.95	3.05	2.71	2.06	1.05	0.70
(x)	EVAR2	1.03	1.32	1.31	1.16	1.03	1.09	1.26	1.33
(xi)	EVAR3	1.43	1.96	2.20	2.10	1.86	1.65	1.37	1.23
(xii)	CMVAR	1.28	1.67	1.73	1.69	1.45	1.13	0.84	0.64
(xiii)	BMVAR	0.93	1.09	1.11	1.09	1.12	1.05	0.94	0.80
(xiv)	BEVAR	0.86	0.97	0.94	0.95	1.02	0.96	0.87	0.79
(xv)	BCVAR	0.96	1.15	1.21	1.22	1.27	1.20	1.09	0.96
(xvi)	BCMVAR	0.87	0.96	0.92	0.92	0.98	0.92	0.84	0.72
(xvii)	Simple Average	**0.71**	0.83	0.74	**0.67**	0.66	0.61	**0.63**	0.62
(xviii)	Trimmed Average	0.74	0.89	0.71	0.75	0.80	0.74	0.64	**0.56**
(xix)	U- Trimmed Average	0.77	**0.82**	**0.71**	0.74	0.85	0.78	0.68	0.57
(xx)	L- Trimmed Average	0.79	1.24	0.89	0.87	0.62	**0.56**	0.66	0.62
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 4 (a) RMSE (Relative to AR(1) model as benchmark) for Jul 2002 to Nov 2007 (Low Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	3.64	2.94	0.56	0.78	0.87	1.06	0.26	0.57
(iii)	ARDL2	2.93	4.45	**0.44**	**0.42**	**0.53**	1.02	**0.18**	**0.36**
(iv)	MVAR1	1.24	1.35	1.20	1.13	1.08	1.09	1.16	1.24
(v)	MVAR2	1.22	1.29	1.21	1.26	1.24	1.24	1.31	1.34
(vi)	CVAR1	1.49	1.89	1.88	2.04	2.24	2.51	2.98	3.83
(vii)	CVAR2	1.83	2.38	2.46	2.81	3.52	4.83	7.32	11.74
(viii)	CVAR3	1.96	2.41	2.53	2.97	3.77	5.12	7.57	11.65
(ix)	EVAR1	1.49	1.37	1.15	1.18	1.36	1.51	1.61	1.64
(x)	EVAR2	1.12	1.15	1.16	1.20	1.20	1.25	1.29	1.35
(xi)	EVAR3	1.59	1.68	1.38	1.61	2.22	3.27	5.05	7.75
(xii)	CMVAR	1.26	1.42	1.29	1.30	1.26	1.29	1.39	1.44
(xiii)	BMVAR	0.98	0.95	0.95	0.95	0.94	0.93	0.93	0.93
(xiv)	BEVAR	1.01	1.01	1.00	1.01	1.00	1.00	1.01	1.00
(xv)	BCVAR	1.02	1.02	1.02	1.04	1.05	1.07	1.10	1.11
(xvi)	BCMVAR	0.99	0.95	0.95	0.95	0.94	0.94	0.95	0.95
(xvii)	Simple Average	0.92	0.98	1.01	1.05	1.11	1.26	1.61	2.24
(xviii)	Trimmed Average	0.91	0.92	0.96	0.99	1.01	1.02	1.04	1.05
(xix)	U- Trimmed Average	**0.71**	**0.72**	0.73	0.72	0.72	**0.78**	0.75	0.77
(xx)	L- Trimmed Average	0.98	1.01	1.03	1.07	1.14	1.31	1.70	2.42
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 4 (b) RMSE (Relative to AR(1) model as benchmark) for Dec 2007 to Jun 2009 (High Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	**0.25**	0.33	0.51	**0.74**	**0.43**	**0.63**	**0.95**	1.14
(iii)	ARDL2	0.26	**0.33**	**0.50**	1.16	0.47	0.78	1.05	**0.86**
(iv)	MVAR1	0.53	0.95	1.42	2.03	2.47	2.94	3.13	2.57
(v)	MVAR2	0.39	0.75	1.21	1.75	1.76	1.56	1.36	1.85
(vi)	CVAR1	0.59	1.07	1.65	2.51	3.34	4.35	5.15	4.70
(vii)	CVAR2	0.60	1.07	1.65	2.50	3.33	4.33	5.12	4.67
(viii)	CVAR3	0.60	1.08	1.68	2.56	3.43	4.50	5.39	4.98
(ix)	EVAR1	0.53	0.99	1.55	2.67	3.88	5.30	6.57	6.08
(x)	EVAR2	0.50	0.88	1.29	1.81	1.75	1.41	1.30	1.28
(xi)	EVAR3	0.57	1.02	1.56	2.57	3.45	4.34	4.83	4.03
(xii)	CMVAR	0.43	0.74	1.06	1.56	2.16	3.02	3.60	2.92
(xiii)	BMVAR	0.48	0.82	1.15	1.55	1.77	1.97	1.93	1.37
(xiv)	BEVAR	0.51	0.92	1.42	2.12	2.75	3.51	3.96	3.41
(xv)	BCVAR	0.51	0.92	1.39	2.03	2.56	3.18	3.54	2.99
(xvi)	BCMVAR	0.47	0.81	1.16	1.60	1.89	2.18	2.24	1.68
(xvii)	Simple Average	0.47	0.83	1.23	1.85	2.34	2.88	3.26	2.82
(xviii)	Trimmed Average	0.48	0.85	1.19	1.99	2.58	3.24	3.47	2.39
(xix)	U- Trimmed Average	0.41	0.68	0.75	1.22	1.70	2.06	2.21	1.22
(xx)	L- Trimmed Average	0.51	0.91	1.22	2.16	2.90	3.68	4.25	3.42
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									

Table: 4 (c) RMSE (Relative to AR(1) model as benchmark) for Jul 2009 to Jun 2014 (Moderate Inflation Regime)

(i)	Model ↓ : h →	3	6	9	12	15	18	21	24
(ii)	ARDL1	1.41	1.67	2.56	3.20	0.68	1.26	1.66	2.57
(iii)	ARDL2	1.35	1.41	1.53	2.10	**0.63**	0.94	1.38	2.31
(iv)	MVAR1	1.16	1.30	1.28	1.18	1.18	1.09	0.92	0.76
(v)	MVAR2	1.30	1.63	1.60	1.43	1.35	1.21	1.06	0.95
(vi)	CVAR1	1.23	1.93	2.79	2.77	2.67	2.50	1.63	1.47
(vii)	CVAR2	1.01	1.09	1.14	1.14	1.16	1.13	1.04	0.98
(viii)	CVAR3	1.13	1.50	1.71	1.55	1.50	1.19	0.98	0.93
(ix)	EVAR1	1.94	2.77	3.45	3.47	3.06	2.47	1.30	0.90
(x)	EVAR2	1.23	1.51	1.53	1.31	1.17	1.31	1.56	1.72
(xi)	EVAR3	1.70	2.26	2.57	2.39	2.10	1.99	1.70	1.58
(xii)	CMVAR	1.53	1.92	2.02	1.92	1.64	1.36	1.04	0.83
(xiii)	BMVAR	1.11	1.25	1.29	1.23	1.27	1.26	1.16	1.04
(xiv)	BEVAR	1.02	1.11	1.10	1.07	1.15	1.16	1.08	1.02
(xv)	BCVAR	1.14	1.32	1.41	1.39	1.44	1.45	1.34	1.24
(xvi)	BCMVAR	1.04	1.10	1.08	1.05	1.11	1.10	1.04	0.93
(xvii)	Simple Average	**0.85**	0.95	0.86	**0.76**	0.74	0.73	**0.77**	0.80
(xviii)	Trimmed Average	0.88	1.02	0.83	0.86	0.91	0.89	0.79	**0.72**
(xix)	U- Trimmed Average	0.92	**0.94**	**0.83**	0.84	0.96	0.93	0.84	0.74
(xx)	L- Trimmed Average	0.94	1.42	1.04	0.99	0.70	**0.68**	0.82	0.80
Bold values are the minimum values at each forecast horizon (i.e. in each column). Bold RRMSE are all less than 1.									