Forecasting Inflation in India Under the Inflation-Targeting Regime

N. Kundan Kishor*
Unversity of Wisconsin-Milwaukee

Abstract

This paper presents an approach to forecasting headline inflation (CPI-Combined) using year-on-year monthly inflation data from 2012:M1 through 2018:M5. To handle instability in the inflation dynamics present in headline inflation, we decompose inflation into a trend and a cycle, referred to as "inflation gap" by Stock and Watson (2007). The results suggest a significant payoff of utilizing this approach. The real-time out-of-sample forecasts from a univariate model of inflation gap significantly outperform the forecasts of the random walk model at all horizons for 2015:M1 through 2018:M5. We also find that exchange rate movements help improve forecasts from the univariate model of inflation gap for short horizons. Most surprisingly, the forecasts from the simple univariate and bivariate models of inflation gap outperform the forecasts reported by professional agencies.

*Kishor: Professor, Department of Economics, Box 413, Bolton Hall 822, University of Wisconsin-Milwaukee, Milwaukee, WI 53201. Email: kishor@uwm.edu.

1 Introduction

The past few decades have witnessed a revolution of transparency in central banking, wherein the central banks routinely make announcements about their policy actions and release forecasts of inflation and other macroeconomic variables. Although no consensus on the merits of transparency in the central banking literature exists, there is broad-based support for the central banks' efforts to provide guidance to the public and the market about their perception of the future movements of inflation. A credible central bank can shape inflationary expectations by signaling its future policy actions and its outlook for future movements in inflation. Unsurprisingly, inflation forecast is of great importance to policymakers, households, and businesses, and the academic literature on forecasting inflation is vast.

Inflation forecasting has become especially important in the Indian context since India's adoption of flexible inflation targeting as a monetary policy strategy in June 2016. As one of the newest entrants to the Inflation Targeting Club, the Reserve Bank of India (henceforth RBI) does not have a long history of officially publishing detailed and comprehensive inflation forecasts. Given the importance of inflation in the overall macro setting, inflation forecasting in India has received prominent attention from both academia and the business sector[1]. Nevertheless, no consensus on the relative usefulness of different inflation-forecasting methodologies has been reached. This lack of agreement can be partly attributed to the instability of inflation dynamics over time[2]. This problem is especially challenging in the Indian context, as shown in Figure 1. For example, headline inflation in India as measured by year-on-year changes in the consumer price index-combined (CPI-C) witnessed a decline from more than 11 percent at the end of 2013 to 2.2 percent in the middle of 2017[3]. The instability of inflation dynamics can create significant challenges

[1] For example, the headline of financial newspaper Livemint on August 7, 2017, read, "Split within RBI flags flawed inflation model." On December 12, 2017, the same newspaper asked, "Has RBI consistently over-estimated inflation in its forecasts?"

[2] See Stock and Watson (2007).

[3] In India, conventionally, the wholesale price index (WPI) has been used to measure headline inflation. In recent years, the RBI, the monetary policy authority in India, has shifted its focus from the WPI inflation to the consumer price index (CPI) inflation. The RBI targets CPI-Combined, a new all India level series introduced in February 2011, by the Central Statistical Organization of India.

for forecasters, and this difficulty is exacerbated by the volatile nature of food and energy prices in India. Unlike many central banks, which focus only on core inflation, the RBI targets headline inflation, which includes food and energy prices[4]. Unsurprisingly, if one performs a horse race between a random walk (henceforth RW) model and a univariate ARMA model, the forecasts from the RW model will be consistently superior in the recent period, suggesting the relative lack of predictability of headline inflation in India[5]. This result is consistent with the findings of Atkeson and Ohanian (2001), who showed that the forecasts from RW models are harder to beat if there is instability in the inflation dynamics.

To circumnavigate the problem of high persistence and instability in inflation dynamics for forecasting, Stock and Watson (2007) suggested decomposing inflation into trend and cyclical components[6]. The underlying idea is to exploit the predictable portion of inflation by focusing on the dynamics of the cycle, referred to as "inflation gap"—the difference between inflation and trend inflation. Once the forecast of the inflation gap is obtained, the forecast of the headline inflation can be computed by simply adding the inflation gap forecast to the estimated trend. Since there is no unique way to decompose a series into a trend and a cycle, the question of which decomposition method to use naturally arises. In the literature can be found two different approaches to estimating trend inflation and inflation gap. The first approach is model-based, and studies that utilize this approach to explicitly model trend inflation or long-term inflation expectations include, for example, Kozicki and Tinsley (2001), Stock and Watson (2010), Cogley, Primiceri and Sargent (2010), and Mertens (2016). Other researchers (e.g., Koenig and Atkinson, 2012; Faust and Wright, 2013; Clark and Doh, 2014) have used survey measures of expectations as an input for their forecasting models. The second approach is motivated by findings that state that surveys often do a better job of forecasting inflation than models based on

[4]See the RBI (2014) expert committee report on the rationale for targeting headline inflation in India.

[5]See Table 1. The details of this exercise are explained in Section 4.

[6]The permanent component or trend is often referred to as the "trend inflation," and there is a broad consensus amongst economists that this component is determined by the behavior of the central bank's monetary policy. Conversely, the transitory variation around the trend is primarily due to firms' price-setting dynamics, external shocks, etc. In the literature, the transitory component is defined as "inflation gap."

macroeconomic and financial variables[7].

Acknowledging that there is no definitive measure of trend and cycle, we use multiple models of trend inflation to forecast inflation in India. In particular, we use four model-based measures and three off-the-shelf measures of trend inflation, or long-term inflation expectations[8]. The model-based measures of trend inflation are based on linear detrending; the Hodrick-Prescott (1997) filter; the Ravn-Uhlig (2002) filter; and the unobserved component model with stochastic volatility (UCSV), as introduced by Stock and Watson (2007). Unlike in the U.S. and other developed countries, there is no consistent approach to conducting surveys long-term inflation expectations in India. In recent years, however, two measures of long-term inflation expectations have garnered some attention. The first survey measure is based on a household survey undertaken by the RBI[9]. We use the one-year-ahead inflation expectation from this survey as a proxy for the long-term inflation expectations for households. The second survey measure of inflation expectations is the five-year median forecast of inflation from the Survey of Professional Forecasters, also conducted by the RBI[10]. We also use core inflation, which excludes food and energy prices, as another measurement of trend inflation.

Armed with different measures of trend inflation, we examine whether there is a payoff in using the inflation gap model to forecast headline inflation in India. First, we use a univariate model of inflation gap and then, in the second stage, we augment the inflation gap model with slack, exchange rates, and minimum support prices. To examine the relative performance of the different models, we perform a genuine, real-time, out-of-sample forecast using information from year-on-year (YoY) monthly inflation data based on the CPI-Combined for the sample period 2013:M1 through 2018:M5[11]. Our forecast sample, 2015:M1–2018:M5, closely aligns with the introduction of the inflation targeting regime. We obtain our benchmark forecasts from the RW model. Unlike the Federal Reserve and

[7] See Ang et al. (2007).

[8] In this paper, the terms "trend inflation" and "long-term inflation expectations" are used interchangeably.

[9] See the details of this survey in the data description section.

[10] Details in the section on data description.

[11] Our sample period is based on the data availability of headline inflation.

the European Central Bank, there is no consistent forecast of inflation produced by the RBI that goes back to the beginning of our sample period. However, we can compare the forecasts generated by our model with those of professional forecasters[12].

The key results are as follows. First, we find that the forecasts from the RW model outperform those of the univariate ARMA model, and the differences in the mean-squared-error (MSE) are statistically significant, according to Clark and West's (2007) nested forecast comparison test. Secondly, we find that the forecasts from the univariate inflation gap model based on different detrending methods strictly outperform the forecasts from the RW model. The survey-based inflation gap model outperforms the RW model for short forecasting horizons but not for longer horizons. Since trend inflation represents the long-term forecast of inflation, it makes intuitive sense to examine its forecasting performance over the medium and long horizons. Unsurprisingly, the forecasting performance of trend inflation without inflation gap is superior to the RW and ARMA models at medium and long horizons (M=6 through M=12). For our forecasting sample period, we do not find the Phillips curve relationship useful in forecasting inflation. Using the monthly industrial production cycle as an estimate of slack, we find that inclusion of this measure in a model of inflation gap does not improve forecasting performance. In fact, in most of the models, the forecasting performance worsens once the slack measure is introduced at different forecasting horizons. However, we find evidence supporting the use of exchange rates as an additional predictor in our inflation gap model, especially for short forecasting horizons. Forecasts from a bivariate model of inflation gap and changes in exchange rates significantly outperform those of the univariate model for short horizons. We also compare the quarterly averages of the forecasts generated by our models with those of the SPF's quarterly forecasts. Surprisingly, the forecasts generated from simple univariate and bivariate VAR models outperform the forecasts from the SPF. The superiority is stronger at the medium and long horizons, which are of greater interest to policymakers.

The remainder of the paper is organized as follows: Section 2 presents the model

[12] These forecasts are made every other month. To compare our forecasts with those of the SPF's, we used forecasts generated in the same month. For details on the timing of these forecasts, see the data description section.

specifications; Section 3 provides a description of the data used in our empirical analysis; Section 4 presents the forecasting results; Section 5 presents the comparison of our forecasts with those of the professional forecasts; and Section 6 presents the conclusion.

2 Model Specification

The premise of our approach is based on the idea that CPI-Combined inflation in India is a highly persistent process. Therefore, it makes sense to adopt the inflation gap approach that has been popularized by Stock and Watson (2007). Using this approach they showed that separating low-frequency movements from the predictable component yields a superior forecast, as it exploits the predictable property of the cyclical component. We can simply add the forecast of this predictable component to the trend to get the forecast of the variable of interest. We do not need to predict the trend component as the best forecast of low-frequency movement or the trend component is the current value of the trend itself. Unlike the RW model, this model exploits the predictability of the cyclical component that is referred to as inflation gap in the literature. The model takes the following form:

$$y_t = \tau_t + c_t$$

where y_t is an I(1) process, and for our purposes, CPI-combined inflation. τ_t is trend component and c_t is cyclical component, and is stationary. Trend is usually modeled as random walk and cycle is modeled as following some ARMA(p,q) process. Cycle in our approach is called inflation gap, as it is the difference between CPI-Combined inflation and trend inflation. In the literature, several methods have been proposed to decompose a non-stationary series into a trend and a cycle. Since there is no consensus on the true model of trend-cycle decomposition, we take an agnostic view in this paper. For our purposes, we use seven different measures of trend inflation. In this paper, four of our measures are based on estimate of trend inflation from different models. For parsimony, we use the linear trend, the HP filter, the Ravn and Uhlig (2002) modification of the HP filter and Stock and Watson's unobserved component model with stochastic volatility (UCSV). The linear trend model is based on deterministic time trend and assumes all the variation in headline inflation is transitory, and hence due to cyclical components. The HP filter is an atheoretical smoothing method to obtain trend and cycle components of non-stationary series and is very popular in macroeconomics and finance literature. We follow the original prescription of Hodrick and Prescott (1997) and use smoothing parameter λ=14400 for our monthly inflation data. Ravn and Uhlig (2002) have suggested using a much higher smoothing parameter for the monthly data. Following their suggestion we use smoothing parameter λ=129600 for the other model. We call this model RU in our exercise. Higher λ yields a much smoother trend. Our last model-based trend is obtained from Stock and Watson's modification of the classic unobserved component model of Clark (1989). Unlike Clark's (1989) model, Stock and Watson's model allows for stochastic volatility in the trend as well as cycle[13]. In particular, trend follows a random walk and cycle has ARMA (p,q) representation. Both trend shocks and cyclical shocks have time-varying volatility

$$\tau_t = \tau_{t-1} + \eta_t, \eta_t \tilde{} iid(0, \sigma^2_{\eta_t})$$

$$c_t = \Phi(L)c_t + u_t, u_t \tilde{} iid(0, \sigma^2_{u_t})$$

Both the trends and the cycles can be easily modified for multivariate cases.

3 Data Description

Our study uses monthly data and runs from 2012:M1 through 2018:M5. The data for headline CPI and index of industrial production and its components are obtained from the Ministry of Statistical Planning and Implementation (MOSPI) website of the Indian government. The inflation rate is calculated as year-on-year percentage changes in headline prices and is annualized. The exchange rate data has been sourced from the FRED database of the Federal Reserve Bank of St. Louis.

We use two survey-based measures of trend inflation or long-horizon inflation expectations. This is motivated by the research in inflation forecasting literature where researchers (*e.g.*, Koenig and Atkinson, 2012; Faust and Wright, 2013; Clark and Doh, 2014) have

[13] For details, see Stock and Watson (2007).

used survey measures of expectations as an input into their forecasting models. Ang *et al.* (2007) show that surveys often do a better job of forecasting inflation than models that are based on macroeconomic and financial variables. In case of India, there are two surveys that explicitly ask for long-run inflation expectations. The first measure is from the RBI's household survey. Since September 2005, the RBI conducts a quarterly inflation expectations survey of households for its internal monitoring[14]. The survey covers 4,000 households using quota sampling, across 12 cities across the four regions of the country. One problem with this survey is that the respondents are more coherent on their perception of current inflation than their expectations of the near future. The second survey that we use in our analysis is RBI's survey of professional forecasters. It is a bimonthly survey and one of the questions in that survey asks the participants about their expectation of CPI-combined inflation 5-years and also 10-years in future. For our purposes, we use 5-year ahead inflation expectation. These surveys are conducted bimonthly since June of 2014. Prior to 2014, these surveys were performed quarterly. As explained earlier, to match the timing with the household forecast we also use the surveys that were conducted in the middle of the quarter. Our final measure of inflation gap is obtained from a model that considers "core" inflation as trend inflation. Core inflation is calculated as percentage annual change in CPI-combined inflation after excluding food and fuel prices.

4 Results

Our sample begins in 2012:M1 and runs through 2018:M5. Our first forecasts cover the period 2015:M1-2015M12 and would have been prepared in 2014:M12 using the information available at the end of 2014. The estimation sample for the first set of forecasts is 2012:M1-2014:M12 and therefore includes 36 monthly observations. We then move forward one month, re-estimate the models based on optimal lag length according to the Schwarz criterion and forecast 2015:M2-2016M1, etc. Our final set of forecasts, are for 2017:M6-2018:M5, would have been prepared in 2017:M5. Note that in this case, we are simply following the conventional real-time VAR estimation where we move along the

[14]https://www.rbi.org.in/scripts/QuarterlyPublications.aspx?head=Inflation+Expectations+Survey+of+Households

columns of the real-time data base for each iteration[15]. Our forecast sample size is 30. The results are presented in terms of the ratio of the root-mean-squared-errors (RMSEs) with random walk model as the benchmark and is in the denominator. Therefore a ratio less than unity implies that the model in question has lower RMSE than the RW model. Our forecast horizon ranges from 1-month ahead (M=1) forecasts to 12-month ahead forecasts. We also consider the average of forecasts over the next 12-months (M=1-12). The average forecasts do not suffer from the noisiness problem associated with the monthly forecasts. In the subsections below, we first present the results for the univariate models of inflation gap and then discuss the forecasting results for VAR models that also contain inflation gap.

4.1 Forecasts Based on Univariate Models of Inflation Gap

Table 1 shows the results for the forecasts obtained from the inflation gap model. First, we compare the results of the forecasts from the RW model with that from an ARMA (p,q) model for CPI headline inflation. The original premise of our approach is that headline CPI inflation is highly persistent in India. Therefore, if we just fit an ARMA(p,q) model that assumes stationarity and perform an out-of-sample forecasting exercise, the forecasts obtained from this stationary ARMA(p,q) model should perform poorly as it forces stationarity as well as stable dynamics on data. The results presented in Table 1 confirm this. The forecasting performance of ARMA(p,q) model is worst at medium horizon and also it performs poorly on average over the next 12-months.

As discussed earlier, we consider seven different models of inflation trend. GAP_LINEAR is the model with inflation gap obtained from linear trend model. GAP_HP is inflation gap is the cycle from Hodrick-Prescott filter. GAP_RU is obtained from the cyclical component of Ravn-Uhlig's modification of the original HP filter. GAP_UCSV is the inflation gap model from the UCSV model of Stock and Watson (2007). GAP_HH is the inflation gap from a model that takes household's year ahead inflation expectation as the trend inflation. This household survey is conducted by the RBI. GAP_CORE refers to the inflation gap from core inflation as a measure of trend inflation; and GAP_SPF is

[15]For an alternative approach on real-time VAR estimation, see Kishor and Koenig (2012, 2014).

inflation gap from a model where we use five-year ahead inflation expectation of Survey of Professional Forecasters as an estimate of trend inflation.

The results clearly show the payoff of using a model that decomposes headline inflation into a trend and cycle, as it uses the predictability of the cyclical component to make prediction for the headline inflation. Except for the inflation gap obtained from the household's inflation expectation and SPF, all the models dominate the RW model in terms of its predictive power. The results from the SPF's inflation gap (GAP_SPF) model and household's survey (GAP_HH) are the same as the RW model. This arises because the inflation gap obtained by taking the difference of headline inflation and inflation expectation from these two surveys are non-stationary, so RW model is also appropriate for the inflation gap. As a result, if the forecasts from these two RW models of inflation gap are added to the trend component, we obtain the forecasts that are exactly the same as the RW model. The non-stationarity problem of inflation gap does not arise in case of model-based inflation gap as by definition the cycles or inflation gap are stationary. On average, forecasts from linear trend and HP trend inflation gap model perform the best, though there is heterogeneity in forecasting performance at different forecast horizons. At the shortest forecast horizons (M=1 and 2), the UCSV model performs best among all the trend inflation models. The improvement in forecasting performance is around 7-8 percent at 1- and 2-month ahead forecast horizons for UCSV model. The improvement in forecast accuracy is huge at longer forecasting horizons for the linear trend and HP trend inflation gap models. We find that at M=9 and 12, we can reduce the RMSE of random walk model by almost 35-40 percent if we use a simple univariate inflation gap model. Even if one uses core inflation as trend, the reduction in RMSE is 20 percent at 12-month ahead forecast horizon.

The interesting finding from the inflation gap model in Table 1 is that the forecasts obtained from this model tend to perform better at longer horizons. The natural question is then, what drives this improvement in forecast improvement? Is it better forecast from inflation gap or a more accurate estimate of inflation trend? To answer this question, we can perform a simple experiment. We can use the estimate of trend inflation at time t as the forecast of headline inflation at time t+h. This assumes inflation gap to be zero at future horizons. The results show that if one is interested in forecasting at 9-month or 12-month ahead, one could do as good a job as inflation trend+gap model as just with a trend model. This is not surprising since by definition inflation gap is stationary, and hence the long-horizon forecast will converge to its unconditional mean that is zero for the model generated cycles (linear, HP, RU and UCSV) trends. The more important finding, in our opinion, is that the estimated trend model strictly dominates random walk model at long horizons. Since random walk model assumes that all the variations are in trend, the results obtained from the model suggests that this is not true in the present context. In fact, our results show that the "true" inflation trend is much smoother than the headline inflation. Looking at the results in Table 2 carefully, we also observe that unlike the inflation gap model in Table 1, if we just use SPF inflation expectation as forecast of headline inflation, we observe improvement in forecast over RW model at longer horizon. In fact, the improvement is almost 25 percent at M=12. Therefore, if one wishes to use inflation expectation from SPF as inflation trend, there is no advantage in trying to forecast the inflation gap. A trend model would end up doing better on average and much better at long-horizons.

4.2 Forecasts Based on Bivariate VAR Models

The results from the univariate models of inflation gap suggest significant improvement in forecasting accuracy for headline inflation in India over a RW model. The next step in our exercise is to examine whether inclusion of another variable is useful in improving the forecasting performance of the univariate model. We use three bivariate models for this purpose: output gap, changes in nominal exchange rate, and changes in minimum support price. The use of output gap is motivated by the Phillips curve relationship. The connection between inflation and real activity has been studied going back at least to Phillips (1958), but remains controversial. The use of exchange rate as another variable for the bivariate VAR model that also contains inflation gap is motivated by the literature where researchers have found that exchange rate plays a role in the evolution of inflation in Indian economy[16]. We also use minimum support price (MSP) changes as another

[16] See Callen and Chang (1999).

variable since MSP has been used regularly as a policy tool in India, and there is some evidence that it affects inflation expectation formation. For each iteration of the estimated VAR model, we choose optimal lag length based on the Schwarz criterion.

The results are shown in Tables 3-5. The results for the bivariate VAR model of inflation gap and output gap as measured by IIP cycle are slightly discouraging. Except for inflation gap obtained from the linear and the HP trends, the forecasting performance worsens for other models at almost every forecast horizon if we include output gap in a model with inflation gap. Even with inflation gap from the linear and the HP trends, the improvement is mainly at short and medium horizons (M=1 through M=6)). The results from this exercise do not suggest that there is no trade-off between inflation and real activity. This result may be an artifact of the choice of output gap[17], or the forecast sample period[18]. The results from the VAR model with nominal exchange rate changes are more encouraging. The inclusion of exchange rate in a model of inflation gap leads to reduction in RMSE for 5 out of 7 bivariate models at short and medium forecast horizons (M=1 through M=6). There is reduction in RMSE at all horizons for the model with the SPF inflation expectation trend. The improvement is higher at longer forecast horizons. If we add changes in minimum support price of crops in the model, the out-of-sample forecasting results are not that encouraging. The inclusion of MSP in almost every model leads to worsening of the forecasts. This suggests for all the alternate models in our study, lags of changes in MSP do not contain any extra information that is already present in the lags of inflation gap.

Overall, the results from VAR model suggest that there is small improvement in forecasting performance if one uses the VAR model with exchange rate. The improvement occurs mainly at short and medium horizons. The results from the VAR exercise presented in our study is rather limited as we consider only three variables. It is possible to find another variable that may contain predictive information about inflation gap.

[17]It is widely known that output gap is notoriously difficult to estimate and there is a great degree of uncertainty around this measure. This problem gets exacerbated in a developing country like India.

[18]This is consistent with Nachane and Lakshmi (2002) and Callen and Chang (1999), who also found that output gap is not a significant predictor of inflation in India. Similarly, Srinivasan et al. (2006) did not find support for the Phillips curve in case of Indian inflation.

5 Comparison of Forecasts with Survey of Professional Forecasters

Our benchmark model for forecast comparison is the RW model. The attractiveness of this model as benchmark lies in its parsimony. However, it is also important to examine the performance of the forecasts generated from these simple univariate and bivariate models in comparison to the forecasts of the professional or official forecasts. Unlike the Federal Reserve or the European Central Bank, there is no consistent time-series of official forecasts of inflation from the RBI. Nevertheless, the RBI undertakes a survey of professional forecasters every month. These forecasts are usually made in February, April, June, August, October and December. Usually the forecasts are reported for the current quarter and 3-quarters in future. To compare our forecasts with the SPF, we match the timing of our forecasts and choose the forecasts that were made at the end of December of previous year, February, April, June, August and October. We lag the forecasts one period backwards to take into the account the delay in publication of the first-release of CPI data. This timing convention puts the models in this paper at slight disadvantage, however, this advantage should disappear at medium and long horizons.

Tables 6 and 7 show the results for this comparison exercise. For the sake of brevity, we only report the results for the univariate inflation gap and the VAR model with exchange rates, as these two models provided the best forecasts in its class among different models that we considered in previous section. Again the results are reported in terms of the ratio of the RMSEs. The results are quite striking and surprising. Forecasts from simple univariate and bivariate model dominate the professional forecasts at almost all forecasting horizons. The good news for the professional forecasts is that it dominates RW model at all forecasting horizons. The surprising finding is that except at short-horizons, even a univariate inflation gap model dominates SPF in terms of lower RMSE. It should be noted that the professional forecasts have timing advantage as these forecasts are made in the middle of the month, whereas the forecasts from our model were generated at the end of the previous quarter. Notwithstanding the timing advantage, the superiority of SPF at short-horizon disappears when the comparison is made with the forecasts from bivariate model of inflation gap and changes in nominal exchange rate. As shown in Table 7, the forecasts from model based inflation gap (linear, HP and RU) dominate the SPF at all horizons except the current quarter whereas most of the inflation trend models dominate at long-horizons. Even though the sample size of forecast sample is only 14, this still suggests that a simple model that takes into account the persistent property of inflation is able to dominate the professional forecasts at almost all forecasting horizons. Surprisingly, if one uses 5-year ahead inflation expectation from SPF as trend inflation, the bivariate VAR model with inflation gap and exchange rate dominates the actual SPF forecasts at long-horizons as shown in the last column of Table 7.

To further examine the relative forecasting performance, we plot the squared forecast error of one-year-ahead forecast errors for four different models in Figure 3. The horizontal axis of the plot shows the time when the forecasts were performed. These models are SPF, RW, the univariate HP inflation gap and the bivariate VAR HP inflation gap and The plot confirms the findings in Tables 6 and 7. The evolution of the forecast error provides us an interesting narrative of how different models have behaved over the last three-years in terms of their forecasting performance. The results show that the SPF was able to capture the decline in inflation in 2015 much earlier than the random walk and the other two model-based forecasts. This is not surprising since the model-based forecasts are based only on the past information of one or two variables. However, SPF forecasts perform significantly worse when they were made during the later half of 2016 and the early 2017. The model-based forecasts have performed significantly better in the later part of the sample.

6 Conclusion

How do we handle instability in inflation dynamics in India for forecasting purposes? We make use of the idea that there is a payoff in exploiting the predictable variation in the cyclical component of inflation after decomposing it into a trend component and a cyclical component. This approach is motivated by Stock and Watson (2007), who decomposed inflation series into two components: a trend, or permanent component, and a cycle, or transitory component. Keeping in mind that there is no unique method to decompose a series into a trend and a cycle, we use model-based trend inflation measures, as well as off-the-shelf measures, such as core inflation and survey-based measures. The results suggest significant a payoff of adopting this approach. Once we add the forecast of the inflation gap—the difference between inflation and trend inflation—to the estimated trend inflation, we find that this forecast significantly outperforms both the RW model and the forecasts from the Survey of Professional Forecasters. The payoff is even more significant at shorter horizons if inflation gap is combined with nominal exchange rate changes, suggesting the exchange rate plays some role in short-term inflationary movements.

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Table 1: Inflation Gap Model

Horizon	RW	ARMA	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF	GAP_BG	GAP_AVG
M=1	1.000	1.072	0.929	0.943	0.930	0.923	0.991	0.934	1.000	0.914	0.925
M=2	1.000	1.100	0.946	0.973	0.948	0.945	1.002	0.933	1.000	0.932	0.931
M=3	1.000	1.128	0.934	0.975	0.938	0.963	1.005	0.925	1.000	0.922	0.934
M=6	1.000	1.216	0.897	0.944	0.899	0.977	1.008	0.988	1.000	0.883	0.902
M=9	1.000	1.194	0.762	0.780	0.758	0.988	1.004	0.951	1.000	0.795	0.830
M=12	1.000	1.193	0.647	0.595	0.631	0.987	1.004	0.793	1.000	0.696	0.786
M=1-12	1.000	1.269	0.712	0.734	0.707	0.970	1.008	0.880	1.000	0.748	0.771

Notes:

The first set of forecasts is for 2015:M1-2015:M12; the final set is for 2017:M6-2018:M5. RW refers to random walk. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's five-year ahead inflation expectation as estimates of trend inflation. GAP_BG and GAP_AVG are combined forecasts from Bates-Granger and simple average methods. M=1-12 refers to the average of 1- through 12-month ahead forecast.

Table 2: Forecast from Trend Inflation

Horizon	RW	ARMA	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF	GAP_BG	GAP_AVG
M=1	1.000	1.072	1.733	1.751	1.734	0.927	3.123	2.127	1.978	1.172	1.515
M=2	1.000	1.100	1.189	1.233	1.193	0.947	2.171	1.503	1.417	1.004	1.131
M=3	1.000	1.128	1.031	1.079	1.036	0.963	1.867	1.283	1.246	0.927	1.021
M=6	1.000	1.216	0.903	0.944	0.905	0.977	1.575	1.051	1.094	0.865	0.934
M=9	1.000	1.194	0.753	0.776	0.750	0.988	1.401	0.902	0.868	0.736	0.826
M=12	1.000	1.193	0.633	0.592	0.619	0.987	1.196	0.707	0.728	0.627	0.718
M=1-12	1.000	1.269	0.707	0.742	0.701	0.970	1.769	0.980	0.974	0.663	0.782

Notes:

The first set of forecasts is for 2015:M1-2015:M12; the final set is for 2017:M6-2018:M5. RW refers to random walk. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's five-year ahead inflation expectation as estimates of trend inflation. M=1-12 refers to the average of 1- through 12-month ahead forecast.

Table 3: VAR Model: Inflation Gap and Output Gap

Horizon	RW	ARMA	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF
M=1	1.000	1.072	0.885	0.911	1.046	0.921	1.002	1.028	1.013
M=2	1.000	1.100	0.864	0.889	1.014	0.946	1.004	1.066	1.003
M=3	1.000	1.128	0.840	0.866	1.051	0.962	0.988	1.065	0.965
M=6	1.000	1.216	0.853	0.870	1.112	0.977	0.979	1.062	0.955
M=9	1.000	1.194	0.806	0.793	1.155	0.989	0.989	0.969	0.846
M=12	1.000	1.193	0.782	0.706	1.151	0.989	0.849	0.822	0.769
M=1-12	1.000	1.269	0.725	0.713	1.203	0.971	0.944	0.985	0.831

Notes:

The first set of forecasts is for 2015:M1-2015:M12; the final set is for 2017:M6-2018:M5. RW refers to random walk. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's five-year ahead inflation expectation as estimates of trend inflation. M=1-12 refers to the average of 1- through 12-month ahead forecast.

Table 4: VAR Model: Inflation Gap and Exchange Rate

Horizon	RW	ARMA	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF
M=1	1.000	1.072	0.906	0.934	1.059	0.929	1.043	1.069	0.959
M=2	1.000	1.100	0.803	0.832	1.064	0.942	1.019	1.050	0.882
M=3	1.000	1.128	0.737	0.770	1.061	0.957	0.991	1.030	0.837
M=6	1.000	1.216	0.849	0.854	1.134	0.975	0.992	1.050	0.934
M=9	1.000	1.194	0.838	0.807	1.212	0.989	0.997	1.000	0.843
M=12	1.000	1.193	0.791	0.700	1.227	0.989	0.850	0.858	0.772
M=1-12	1.000	1.269	0.711	0.672	1.261	0.970	0.948	0.991	0.783

Notes:

The first set of forecasts is for 2015:M1-2015:M12; the final set is for 2017:M6-2018:M5. RW refers to random walk. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's five-year ahead inflation expectation as estimates of trend inflation. M=1-12 refers to the average of 1- through 12-month ahead forecast.

Table 5: VAR Model: Inflation Gap and Minimum Support Price

Horizon	RW	ARMA	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF
M=1	1.000	1.072	1.030	1.062	1.897	0.944	1.074	1.082	1.023
M=2	1.000	1.100	0.993	1.041	1.979	0.955	1.024	1.044	0.995
M=3	1.000	1.128	0.974	1.037	2.064	0.969	1.005	1.028	1.005
M=6	1.000	1.216	0.900	0.996	2.196	0.974	1.065	1.104	1.121
M=9	1.000	1.194	0.850	0.931	2.174	0.985	1.169	1.143	1.096
M=12	1.000	1.193	0.774	0.806	2.061	0.985	1.037	1.012	0.995
M=1-12	1.000	1.269	0.795	0.911	2.512	0.968	1.115	1.118	1.072

Notes:

The first set of forecasts is for 2015:M1-2015:M12; the final set is for 2017:M6-2018:M5. RW refers to random walk. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's five-year ahead inflation expectation as estimates of trend inflation. M=1-12 refers to the average of 1- through 12-month ahead forecast.

Table 6: Comparison of Inflation Gap Model with Professional Forecasters

Horizon	RW	PROF	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF	GAP_BW	GAP_AVG
Q=1	1.000	0.571	0.651	0.632	0.647	0.710	0.781	0.693	0.781	0.638	0.653
Q=2	1.000	0.806	0.817	0.912	0.827	0.856	0.869	0.828	0.869	0.785	0.795
Q=3	1.000	0.819	0.836	0.876	0.837	0.831	0.845	0.788	0.845	0.718	0.775
Q=4	1.000	0.711	0.583	0.586	0.575	0.873	0.879	0.718	0.879	0.632	0.685
Q=1-4	1.000	0.742	0.661	0.704	0.660	0.850	0.872	0.727	0.872	0.654	0.682
Q=2-4	1.000	0.760	0.668	0.714	0.667	0.846	0.859	0.728	0.859	0.649	0.688
Q=3-4	1.000	0.742	0.644	0.662	0.639	0.842	0.852	0.711	0.852	0.634	0.680

Notes:

These forecasts are made every other month and the timing coincides with the SPF forecasts. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's 5-year ahead inflation expectation as estimates of trend inflation. GAP_BG and GAP_AVG are combined frorecasts from Bates-Granger and simple average methods. Q=1-4 refers to the average of 1- through 4-quarter ahead forecasts.

Table 7: Comparison of Inflation Gap+Exchange Rate VAR Model with Professional Forecasters

Horizon	RW	PROF	GAP_LIN	GAP_HP	GAP_RU	GAP_UCSV	GAP_HH	GAP_CORE	GAP_SPF	GAP_BW	GAP_AVG
Q=1	1.000	0.571	0.711	0.712	0.963	0.718	0.840	0.835	0.750	0.661	0.703
Q=2	1.000	0.806	0.488	0.608	0.694	0.849	0.910	0.980	0.814	0.553	0.584
Q=3	1.000	0.819	0.624	0.650	0.767	0.827	0.906	0.956	0.788	0.555	0.617
Q=4	1.000	0.711	0.610	0.580	0.933	0.874	0.804	0.824	0.722	0.636	0.676
Q=1-4	1.000	0.742	0.479	0.504	0.891	0.847	0.878	0.925	0.734	0.524	0.558
Q=2-4	1.000	0.760	0.480	0.506	0.834	0.844	0.851	0.906	0.729	0.517	0.556
Q=3-4	1.000	0.742	0.563	0.550	0.872	0.841	0.828	0.864	0.717	0.571	0.608

Notes:

These forecasts are made every other month and the timing coincides with the SPF forecasts. GAP_LIN, GAP_HP, GAP_RU, GAP_UCSV are inflation gap models from linear detrending, the HP filter, the Ravn-Uhlig filter, and the UCSV model. GAP_HH, GAP_CORE AND GAP_SPF use household's inflation expectation, core inflation and SPF's 5-year ahead inflation expectation as estimates of trend inflation. GAP_BG and GAP_AVG are combined forecasts from Bates-Granger and simple average methods. Q=1-4 refers to the average of 1- through 4-quarter ahead forecasts.

Figure 1: Headline Inflation (CPI-Combined)

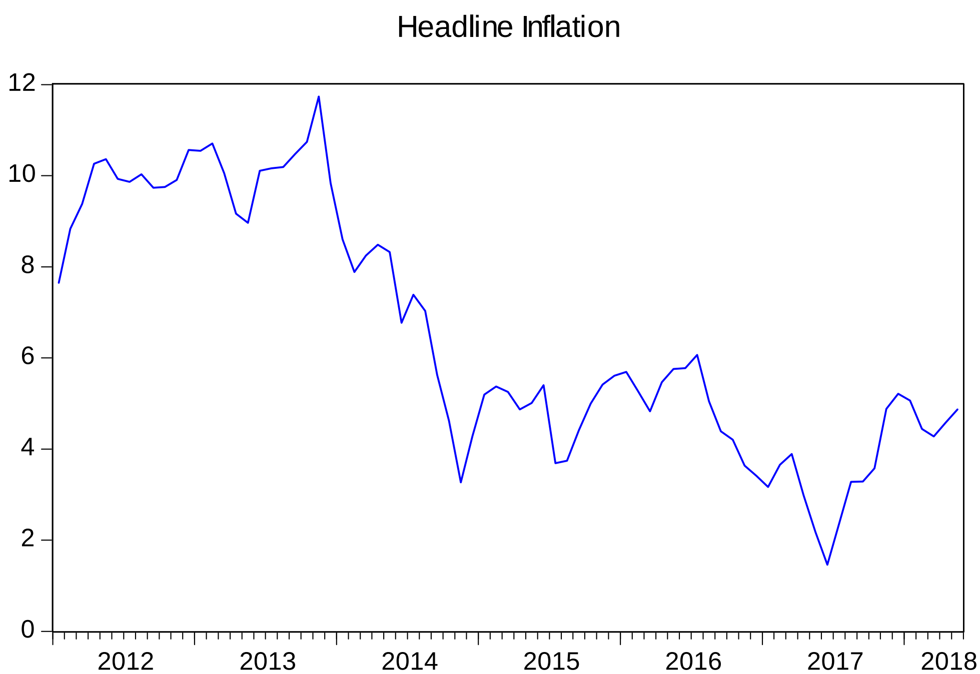

Figure 2: Headline Inflation with Different Measures of Trend

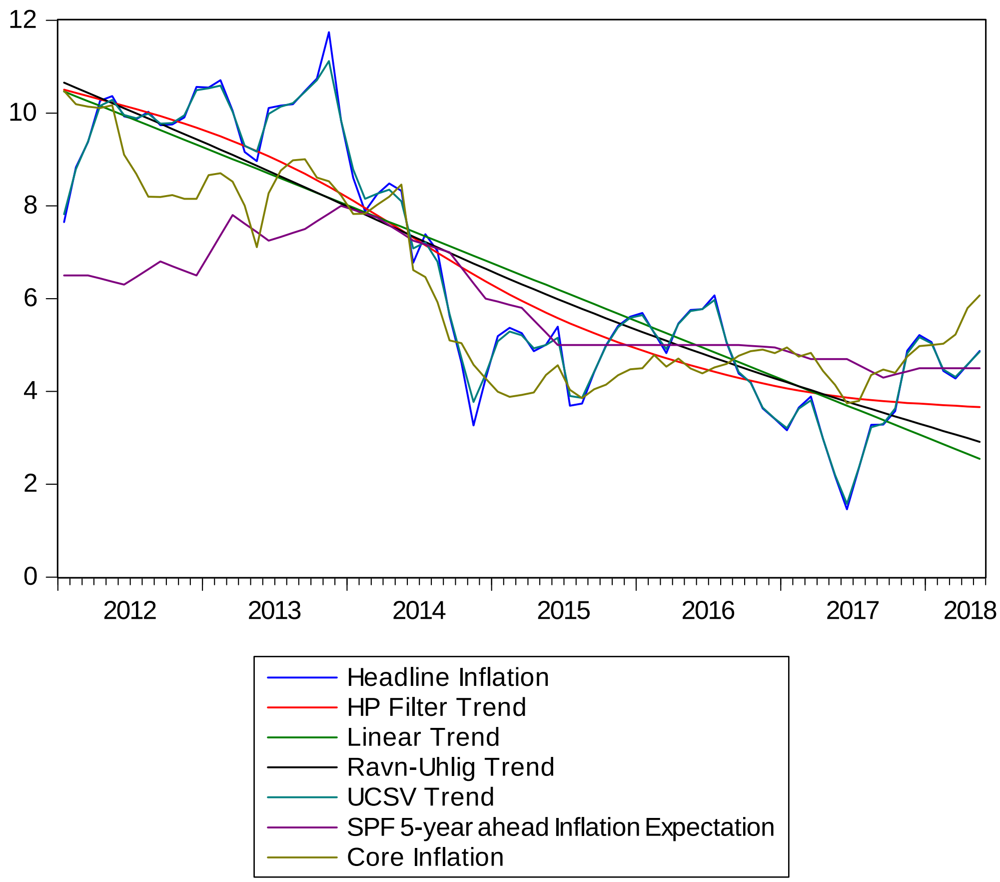

Figure 3: Average 1-year Ahead Squared Forecast Errors for Different Models