The Role of Inflation Targeting in Anchoring Long-Run Inflation Expectations: Evidence from India

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Abstract

This paper investigates the impact of the Reserve Bank of India's (RBI) adoption of inflation targeting (IT) in 2016 on anchoring long-term inflation expectations. Utilizing data from 2010 to 2022, including forecasts by 14 professional forecasters and an inflation sentiment index derived from newspaper articles, we examine the responsiveness of long-term inflation expectations, as measured by the common trend in inflation forecasts, to inflation sentiment before and after IT adoption. Before IT adoption, long-term inflation expectations were very reactive to sentiment changes. After IT, their sensitivity to such sentiment notably decreased.

Keywords: Inflation Targeting, Inflation Expectations, Unobserved Component Model, Inflation Sentiment, Indian Economy

JEL Codes: E31, E52,E58.

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1 Introduction

The adoption of inflation targeting (IT) as a monetary policy framework has gained considerable popularity across the global economy in recent decades. This shift in central banking practices, initially pioneered by the Reserve Bank of New Zealand in 1990, has since been embraced by central banks in 32 countries as their primary strategy for achieving and maintaining price stability. One of the most recent entrants to this club, the Reserve Bank of India (RBI), officially joined the ranks of IT practitioners in 2016, marking a significant policy transformation in one of the world's most populous and dynamically evolving economies.

India's implementation of IT is significant in the global economic landscape. As the world's most populous and fifth-largest economy, India's monetary policy decisions impact global economic stability and growth. The success or failure of IT in India could influence other developing economies, potentially reshaping global monetary policy. India's unique economic structure, with its large informal sector and sensitivity to agricultural output, presents challenges for IT, offering insights into its adaptability across diverse economic conditions as emerging markets play an increasingly important role globally. In a period of global uncertainty, including trade tensions and the COVID-19 pandemic aftermath, assessing IT's effect on long-term inflation expectations in India is crucial. Research in other emerging markets like Brazil, Chile, and South Africa has shown that IT can effectively anchor inflation expectations, contribute to macroeconomic stability (Levin *et al.*, 2004; Mishkin and Schmidt-Hebbel, 2007; Gonçalves and Salles, 2008), reduce inflation persistence, and help stabilize expectations, even amid external shocks (Carare and Stone, 2006). However, India's unique challenges make it an important case study for assessing the broader applicability of IT in diverse economic contexts.

As India's IT regime evolves and matures, assessing its effectiveness in achieving its primary objectives becomes crucial. A particularly important aspect of this assessment is the anchoring of long-term inflation expectations, which significantly influence the behavior of economic agents, including consumers, businesses, and investors. Well-anchored expectations align closely with the central bank's inflation target, fostering a stable economic environment. Extensive research, particularly in developed economies, has shown that a successful IT regime should lead economic agents to adjust their predictions to align with the central bank's target. This alignment helps anchor expectations, reducing the impact of short-term fluctuations. As Bernanke (2003) emphasizes, anchored inflation expectations remain stable despite short-term economic changes, reflecting the credibility of the central bank's commitment to its target. In a recent paper, Bundick and Smith (2023) provide a theoretical framework and empirical evidence in support of the hypothesis that a successful IT regime leads to anchoring of long term inflation expectations in form of expectations about inflation far in the future no longer responding to unexpected changes in current inflation. [1].

India's transition to an IT framework represents a critical policy shift, especially given its unique economic and institutional context (Chakravarty, 2020; Dua, 2023). Analyzing how this transition has influenced the expectations of private sector forecasters at different horizons is essential for understanding the adaptability and effectiveness of IT in an emerging market like India. Despite the growing body of research on IT in emerging markets, India's unique economic challenges pose a different set of challenges in understanding IT's impact on long-term inflation expectations. This study aims to fill this gap by examining how IT has influenced professional forecasters' inflation expectations in India.

To examine the impact of India's inflation targeting (IT) regime on inflation expectations, this paper utilizes a dataset of professional forecasters' one-year-ahead inflation expectations from January 2010 to October 2022. Additionally, it introduces a novel, high-frequency inflation sentiment index, developed using natural language processing (NLP) techniques applied to Indian newspaper articles. The empirical approach decomposes one-year-ahead inflation expectations into a long-term trend, reflecting long-horizon expectations, and a cyclical component capturing short-term fluctuations (Blanchard and Bernanke, 2023), using a multivariate unobserved components (UC) model. This methodology adapts the Stock and Watson (2007) framework by incorporating the concept of the inflation gap—the deviation of actual inflation from its trend—as the cyclical component. Capturing short-term movements in inflation with an autoregressive cyclical component is widely used in the literature on monetary policy credibility and forecasting, as evidenced in the works of Cogley *et al.* (2010); Faust and Wright (2013); Morley *et al.* (2015), among others.

One significant advantage of using a panel of private sector forecasters in our setup is the ability to measure long-horizon expectations as a common long-term trend and short-term inflation expectations as a common cycle across all forecasters. This approach is supported by evidence that these forecasts share a common long-term trend, indicating cointegrating relationship in these forecasts. Deviations from this trend are stationary, with a portion being common across forecasters and another portion being idiosyncratic. Incorporating multiple forecasters into this UC model enhances the precision of our estimates, as suggested by Basistha and Nelson (2007); Basistha and Startz (2008). Similarly, Kishor and Koenig (2022) demonstrate that using a multivariate unobserved-components model improves the

[1] See also Clark and Davig (2008), Kozicki and Tinsley (2012)

accuracy of inflation forecasts by leveraging multiple data sources. Indeed, we find that attempting a univariate decomposition of the median inflation forecast from another survey leads to identification issues when trying to separate trend from cycle.

In the second step of our analysis, we employ local projections to estimate the response of long-run and short-run inflation expectations to incoming data, captured by our novel inflation sentiment index. This index, created using text-mining techniques applied to a comprehensive dataset of news articles from leading business dailies in India, represents another contribution of this paper. Unlike traditional methods that rely solely on quantitative economic indicators, our approach integrates qualitative insights from media reports, providing a richer perspective on inflation expectations.

To construct the index, we collected daily news items from five major business newspapers, filtering them for relevant inflation-related keywords. After cleansing the data, we applied a lexicon-based sentiment analysis, using the Loughran-McDonald lexicon and adjusting for valence shifters. This method ensures accurate sentiment scoring, which correlates well with headline inflation and provides predictive insights. By applying the state-dependent impulse response analysis method from Jordà (2005), we capture varying impacts of inflation sentiment across different monetary policy regimes, highlighting one of the contributions of our study.

We find that the private sector forecasters' long-run inflation expectations, as measured by the inflation trend, began to moderate before the formal introduction of the IT regime. These long-run inflation expectations stabilized around the inflation target of 4 percent after the adoption of the IT regime, where the unconditional mean of deviation of long-term inflation expectations from the 4 percent inflation target is not significantly different from zero. Before the implementation of IT, long-term inflation forecasts, measured by the common trend in 1-year-ahead predictions, were highly responsive to changes in inflation sentiment, reflecting susceptibility to economic news and developments. After adopting IT, this reactivity markedly decreased, leading to long-horizon inflation expectations becoming unresponsive to inflation sentiment. The response of short-term inflation expectations to inflation sentiment remained unchanged between the pre-IT and post-IT periods. These results offer insights into the effectiveness of India's transition to an IT framework in influencing inflation expectations among private sector forecasters. By showing that long-term inflation expectations have become less sensitive to inflation sentiment in the post-IT regime period, our paper suggests that the policy shift may have indeed contributed to the anchoring of long-term inflation expectations, aligning them more closely with the central bank's inflation target.

The decline in inflation expectations in India following the adoption of inflation targeting in 2016 is unlikely to be attributed to global factors. In a paper focusing on India's disinflation in the post-2014 sample period, Chinoy et al. (2016) found limited role of global factor in disinflation in India during this time period. This is also evidenced by the lack of synchronization between India's inflation dynamics and those of other inflation-targeting nations, as shown in Table 1. The table highlights that India's inflation trends remain relatively unsynchronized with both developed and other emerging markets, with low or even negative correlations, such as -0.14 with Brazil. Unlike developed economies, where inflation rates tend to move in tandem due to common global influences, India's inflation trends are driven by domestic factors like food prices, supply-side constraints, and fiscal policies. The complex subsidy structure and fiscal policies in India often impede the transmission of global price changes, including oil prices, to domestic inflation.[2]

Our finding that long-run inflation expectations have changed significantly and become less sensitive to inflation sentiment shocks is robust across different model specifications. These robustness checks include allowing for breaks in the variance of shocks to long-run and short-run inflation expectations, and utilizing a different variant of a dynamic factor model. We also account for global inflation measures in our impulse response analysis, specifically controlling for global food prices, global oil prices, and global CPI inflation. The robustness of our results to these additional controls implies that the response changes across the two regimes are stable.

The remainder of the paper is organized as follows: Section 2 provides background on India's adoption of the inflation targeting regime and reviews the related literature. Section 3 describes the forecast data and the construction of the inflation sentiment index. Section 4 presents the trend-cycle decomposition model employed in our analysis. Section 6 examines the response of long-term and short-term inflation expectations to inflation sentiment shock, while Section 7 presents robustness checks. Finally, Section 8 concludes.

[2] In addition to observed inflation, we also examine the correlation between 1-year-ahead inflation expectations of professional forecasters for a set of countries, finding little comovement with inflation expectations in India. We also test for cointegration and we do not reject the null of no cointegration for median 1-year ahead inflaiton expectations for a set of six inflation targeters: Australia, Brazil, Chile, Colombia, India and New Zealand. This provides further evidence in support of the hypothesis that reduction in inflation expectations in India post-2016 reflects the impact of targeted domestic policies rather than global disinflationary trends.

2 Background and Related Literature

2.1 Background

The history of monetary policy strategy in India has witnessed significant evolution over the years.[3] The Reserve Bank of India (RBI), established in 1935, is responsible for the conduct of monetary policy in India. Throughout its long history, the RBI's role as the monetary authority has continued to evolve in line with the needs of the Indian economy as well as broader academic consensus on the role and conduct of monetary policy over the years. During the planned development process of the nation, the RBI's role evolved towards regulating credit availability to align with the country's developmental needs. With the nationalization of major banks in 1969, the central bank aimed to regulate credit to support the nation's planned development goals, often using the *Cash Reserve Ratio* (CRR) as a tool.

However, the 1970s and the mid-1980s saw the monetization of fiscal deficits and inflationary pressures due to increased public expenditure, leading to frequent adjustments of the CRR. Following the high volatility of prices in the 1970s, the Indian government appointed a committee led by the late Sukhamoy Chakravarty in 1982 to examine the workings of the RBI and suggest appropriate monetary policy strategies for the central bank. The RBI adopted a monetary targeting strategy following the recommendations of the *Chakravarty* committee report in 1985. The *Chakravarty* committee's recommendations were influenced by the successful adoption of monetary targeting by the central banks in Europe, mainly the Bundesbank. The RBI followed the explicit monetary targeting strategy until 1998. In the context of the increasing deregulation of the Indian economy, the RBI's *Working Group on Money Supply 1998* observed that monetary targets could lack precision in a rapidly changing economy. As a result, the RBI adopted a multiple indicator approach after 1998-1999, whereby a set of economic variables was monitored along with the growth in broad money.

The monetary policy framework continued to evolve, and over 2014 to 2016, in a series of steps, India transitioned to an inflation targeting (IT) framework. The route for the adoption of FIT framework in India was paved with the setting up of the *Expert Committee to Revise and Strengthen the Monetary Policy Framework* by Dr. Raghuram Rajan, then Governor of the RBI, in September 2013. The Expert Committee chaired by Dr. Urjit R. Patel submitted its final report in January 2014 recommending a shift to inflation targeting

[3]See Patnaik and Pandey (2020), Chakravarty (2020), Dua (2023) and Ghate and Ahmed (2023) for a detailed review of the monetary policy framework in India, including the transition to inflation targeting.

along with broad measures to facilitate this transition. The move towards inflation targeting was strengthened by the signing of the *Monetary Policy Framework Agreement* (MPFA) between the Government of India and the RBI in February 2015. This was followed by an official amendment to the *RBI Act, 1934* in May 2016 to provide a statutory basis for the implementation of the IT framework, aligning India with a growing list of countries adopting inflation targeting as their monetary policy framework. Under the IT framework, the inflation target was set at 4% with a tolerance band of +/- 2%. This shift towards IT also involved the establishment of a six-member Monetary Policy Committee (MPC) responsible for setting the policy repo rate. The first meeting of the MPC was held in October 2016. Figure 1 shows the monthly CPI headline inflation rate for India since 2010, highlighting important milestones in its transition to the IT regime. For a thorough assessment of India's experience and performance under the IT framework through its initial five years from 2016 to 2021, refer to Eichengreen *et al.* (2021) and Reserve Bank of India (2021). Overall, India's shift to the IT framework has been marked by higher transparency, improved policy communication, and better anchoring of inflation expectations, along with low and stable inflation Mathur and Sengupta (2019); Das *et al.* (2020); Samanta and Kumari (2021).

2.2 Brief Literature Review

The literature on the impact of inflation targeting (IT) on macroeconomic outcomes is extensive, with a particular focus on how IT influences the anchoring of long-run inflation expectations. Anchoring long-run inflation expectations is crucial within the context of IT because well-anchored expectations instill confidence among economic agents—households, businesses, and investors—that future inflation will remain close to the central bank's target. This confidence influences their decisions regarding wage and price setting, which in turn impacts actual inflation outcomes.

In a seminal work on the effectiveness of IT, Svensson (2010) emphasizes the importance of credible commitment in anchoring expectations. He argues that IT requires a central bank's commitment to maintaining price stability, which should, in turn, stabilize long-term expectations. Bernanke (2003) further highlights the central role of inflation expectations in shaping monetary policy, arguing that a credible IT regime should render long-run expectations insensitive to incoming data. This view is supported by Gürkaynak *et al.* (2005), who examine how long-term interest rates respond to economic news, indirectly influencing inflation expectations. Their findings underscore the importance of a credible IT framework in mitigating the volatility of expectations. The role of communication in shaping household's expectations about monetary policy has also been highlighted by Carvalho and Nechio (2014).

Cross-country evidence by Gürkaynak *et al.* (2006) indicates variability in the effectiveness of IT in anchoring expectations across different nations, with some countries achieving stable expectations and others experiencing sensitivity to economic news. Mishkin and Schmidt-Hebbel (2007) emphasize the critical role of effective communication in shaping expectations, suggesting that clear communication of policy goals is essential for anchoring inflation expectations. The literature on IT in emerging markets also underscores the importance of a strong institutional framework and the role of the expectations channel in the success of IT regimes (Batini and Laxton, 2006). Evans and Honkapohja (2001) underscore that managing expectations is central to achieving policy objectives, as expectations directly influence economic outcomes. Carvalho *et al.* (2023) evaluates the degree of anchoring in the US and Japan, among other countries.They argue that, in contrast to Japan's experience, professional forecasters' inflation expectations became generally well anchored in the US by the late 1990's. It is worth noting, as highlighted by Bonomo *et al.* (2024) in the case of Brazil, that inflation expectations can quickly become unanchored if the central bank weakens its commitment to the inflation target. This underscores the importance of maintaining strong institutional credibility to ensure the long-term success of inflation targeting regimes.

In the Indian context, several studies have assessed the impact of IT on inflation expectations. Chinoy *et al.* (2016) provide early evidence on IT's role in reducing inflation, attributing about one-third of India's post-2014 disinflation to the IT framework. Asnani *et al.* (2019) utilize survey data to demonstrate that IT has successfully anchored household inflation expectations, with limited spillover effects from volatile components like food inflation. More recently, Pattanaik *et al.* (2023) employ an inflation expectations anchoring index, using aggregate household data to show enhanced performance in anchoring expectations following IT adoption. Similarly, Garga *et al.* (2022) analyze financial markets' expectations and find that IT was perceived as a credible commitment by the Reserve Bank of India (RBI), leading to a more robust monetary policy reaction to inflation.

While the literature generally supports IT's effectiveness in anchoring expectations, it also highlights potential challenges. For example, Coibion and Gorodnichenko (2012) challenge the assumption that IT alone can address issues like asset price bubbles or supply-side shocks, suggesting that additional policy tools may be required. They argue that the interplay between monetary policy, trend inflation, and expectations is complex and that changes in expectations are closely linked to actual inflation.

Another strand of the literature focuses on the role of inflation targeting in managing expected inflation levels. Johnson (2002) finds that the announcement of inflation targets typically leads to a decline in expected inflation, a trend that persists even after controlling for various factors. However, the impact of IT on the variability of expectations and forecast accuracy is less clear. Some studies suggest that while IT stabilizes the level of expected inflation, it may not significantly reduce its variability or improve forecast precision. This nuance highlights that IT's primary function may be in managing the level of expected inflation rather than its variability.

The transition to a flexible average inflation-targeting (FAIT) regime, as examined by Naggert *et al.* (2021), provides insights into how adopting new monetary policy frameworks can further influence the anchoring of expectations. Their findings suggest that FAIT can help stabilize inflation expectations more effectively. Similarly, Gülsen and Kara (2021) Kara (2021) emphasizes the importance of policy performance in shaping expectations, arguing that the effectiveness of inflation targets depends heavily on the credibility and performance of the policy itself.

Our paper contributes to the literature on the impact of IT by employing advanced text mining techniques to analyze the effects of news about inflation on inflation expectations. We construct a novel inflation sentiment index using daily news items from five leading business newspapers in India, applying a lexicon-based approach with valence-shifting bigrams. This method, inspired by Ardia *et al.* (2021) and utilizing the Loughran-McDonald lexicon, enables us to capture nuanced sentiments in economic and financial texts. By integrating this sentiment analysis with traditional econometric methods and survey data, we offer fresh insights into the anchoring of inflation expectations within the context of IT regimes. Our approach provides a more granular understanding of how inflation-related news influences professional forecasts in both the long-term and short-term, thereby enhancing the assessment of monetary policy transmission in the digital age.

Additionally, our work is related to the literature on trend inflation and the inflation gap, where trend inflation measures the slow-moving permanent component of inflation, and the inflation gap reflects the transitory component. This approach, which modifies the original Stock and Watson (2007) model, has been widely applied in studies on monetary policy credibility and forecasting, as seen in the works of Cogley *et al.* (2010), Faust and Wright (2013) and Kishor and Koenig (2022), among others. We extend this literature by accounting for the multivariate properties of a panel of forecasts, capturing the common permanent component as a measure of long-run inflation expectations and a common transitory component as short-term inflation expectations. The idea of using panel of forecasters to obtain an estimate of long-term inflation expectations has also been explored in a recent study by Fisher *et al.* (2023). Using forecasts for U.S. inflation, they emphasize the importance of using panel data from professional forecasters to capture long-run inflation expectations. They argue that use of information from panel of forecasters allows one to account for biases and overconfidence in individual forecasts, which can lead to more robust and coordinated long-term expectations.

By combining these approaches— a multivariate UC model for decomposition of professional inflation forecast and sentiment analysis of news content-our study provides a framework for evaluating the effectiveness of IT regime in anchoring inflation expectations in Indian economy.

3 Data and Preliminary Evidence

3.1 The Data

Our data comprises multiple sources, including inflation expectations, a measure of inflation sentiment based on news articles, and other major macroeconomic variables for the Indian economy. To estimate inflation expectations, we utilize a dataset compiled by Consensus Economics, a London-based economic survey organization (http://www.consensuseconomics.com/). This organization conducts monthly surveys by soliciting input from experts representing both public and private economic institutions, primarily comprising investment banks and economic research institutes. While the dataset covers all major macroeconomic variables, we utilize monthly forecasts of current year and upcoming year of consumer price inflation (CPI, YoY%) for our purpose.[4] It is also noteworthy that neither central banks nor governments are involved in this survey process. These expert forecasters are situated in the respective countries for which they are providing their forecasts. Although Consensus Forecasts reports headline inflation forecasts for India prior to 2010, the entry and exit of forecasters during the earlier years limit the feasibility of starting the sample earlier. For instance, in 2009, only nine forecasters provided inflation forecasts for the current year and 1-year ahead, and three of these forecasters subsequently dropped out of the sample. We observe a significantly higher number of forecasters contributing to the Indian economy fore-

[4]In the survey, CPI-Industrial Workers (CPI-IW) was replaced with CPI-All India Combined (CPI-C) starting in February 2015.

casts in more recent periods, reflecting India's growing importance in the global economy. Additionally, selecting 2010 as the starting point ensures a more balanced distribution of pre-IT and post-IT observations, allowing for a more robust analysis of the impact of inflation targeting. We retain only those forecasters in our sample which (i) provided inflation forecasts both before and after 2014; and (ii) reported at least 60 percent of the full sample forecasts across time, including forecasts for both current and next year.[5] Out of all professional forecasters in the survey, a total of 14 forecasters meet the above criteria and are included in our dataset spanning from January 2010 to October 2022, encompassing a total of 154 monthly observations, with missing observations for some participants.

To address the issue of missing observations in our dataset, we implement a non-parametric, machine learning (ML) algorithm for imputation. Specifically, we employ the *MissForest* imputation algorithm proposed by Stekhoven and Buhlmann (2012). The algorithm begins by making an initial guess for all missing values in a dataset, such as mean values for continuous variables or mode values for categorical variables. Following this, a *random forest* (RF) model is trained on the observed data, treating the variable(s) with missing values as the target variable(s) and all other variables as predictors. The trained model is then used to predict the missing values. This process is iterative, with the algorithm cycling through each variable in the dataset, updating the imputed values with predictions from the RF model. The iterations continue until a predefined stopping criterion is met, typically when the difference between consecutive imputations stabilizes, indicating that further iterations would not lead to significant changes in the imputed values. Alternatively, the process can be set to stop after a maximum number of user-defined iterations is reached. The *MissForest* algorithm is particularly advantageous due to its ability to handle complex interactions between variables and its robustness to noisy data. Moreover, its non-parametric nature makes it flexible and capable of capturing non-linear relationships within the data, which is often the case with macroeconomic variables, such as inflation forecasts. By leveraging information across both the cross-sectional and time dimensions of the dataset, this method provides us with a complete and reliable panel of inflation forecasts across different horizons.[6]

[5]It may be noted that if a forecaster missed even a single month of forecasts over the more than 12 years covered in our sample, that forecaster was classified as having a missing observation. This is a very stringent criterion, and unsurprisingly, only one forecaster in the sample has reported without missing a single month. We also perform a robustness check with cutoffs of 70 percent and 80 percent, the overall distribution of the forecasts remains consistent (see Figure C1 in Appendix C).

[6]The algorithm is implemented using the *missForest* R package. Appendix C provides more details on the algorithm. Interested readers may also refer to Stekhoven (2011) and Stekhoven and Buhlmann (2012) for details on the algorithm.

The survey participants offer their projections for both the current and the upcoming calendar year. Consequently, the survey data generates a series of fixed-event forecasts. We adopt fixed horizon forecasts in our analysis to ensure comparability with a significant body of existing literature, including the work of Mankiw *et al.* (2003). In line with the approach taken by Dovern *et al.* (2012), we approximate fixed-horizon forecasts as a weighted average of fixed-event forecasts as follows: Let $\widehat{x}_{t+k,t}$ represent the forecast for variable x, k months ahead, based on the information available at time t. Within the survey data, for each month, we encounter a pair of forecasts, $\{\widehat{x}_{t+k,t},\ \widehat{x}_{t+k+12,t})]$, spanning a 12-month horizon. To approximate the fixed horizon forecast for the subsequent twelve months, we compute an average of the forecasts for the current and next calendar year, with weights determined by their respective contributions to the forecasting horizon:

$$\widehat{x}_{t+12,t} = \frac{k}{12}\widehat{x}_{t+k,t} + \frac{12-k}{12}\widehat{x}_{t+k+12,t}$$

As explained in Dovern *et al.* (2012), the November 2018 forecast of inflation rate between November 2018 and November 2019 is approximated by the sum of $\widehat{\pi}_{2018:12,,2018:11}$ and $\widehat{\pi}_{2019:12,,2018:11}$ weighted by $\frac{2}{12}$and $\frac{10}{12}$, respectively.

For robustness checks, we also utilize a survey of professional forecasters conducted by the RBI that provides a median estimate of their 1-year ahead inflation forecasts. This survey has been conducted bimonthly since June 2014, following a quarterly frequency prior to that. The survey was originally conducted on a quarterly basis, but it was switched to a bimonthly frequency in 2014-15 to better align with the RBI's monetary policy cycle. Although individual-level forecasts are not publicly available, the aggregate data provides valuable insights into professional forecaster's expectations. For our analysis, the bimonthly data was converted into quarterly figures by averaging the forecasts when more than one data point was available within a quarter. To ensure consistency with data from Consensus Forecasts, we use 1-year-ahead inflation forecasts from this data source for our study when examining the univariate decomposition of inflation forecasts.

The RBI also publishes household inflation expectations. Since September 2005, the RBI has conducted a quarterly inflation expectations survey of households for internal monitoring[7]. This survey, using quota sampling, covers 4,000 households across 12 cities in the country's four regions. One problem with this survey is that respondents have a clearer perception of current inflation than their expectations for the near future. Research indicates that the inflation expectations of households are consistently higher than the actual

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

inflation rates that follow. This pattern is not unique to India and has been observed in other countries as well (see Das *et al.* (2016) and Verbrugge and Zaman (2021)).

Unlike in developed countries, India lacks a consistent measure of market-based inflation expectations. Our measure of inflation expectations improves upon this aggregated measure by the RBI as it allows us to track each forecaster over our sample period. In addition, the literature also shows the superiority of private sector inflation expectations. For example, Verbrugge and Zaman (2021) found that the expectations of professional economists and businesses provided more accurate predictions of future inflation than those of households and financial market participants.

3.2 Inflation Sentiment Index

To construct a measure of inflation news, we collect daily news items from five leading business news dailies published during January 2010 to December 2021. The newspapers are selected based on their national coverage and reporting of macroeconomic issues.[8] In the first step, we categorize and select articles related to inflation by using keyword searches. Only those news items which contain at least one word from our inflation keyword set, which includes words like "consumer price index", "inflation", "headline inflation" etc., are retained for our analysis. [9] Filtering news articles this way ensures that only articles containing contextually relevant and meaningful information are used in our analysis. Following this, standard data cleansing procedures are applied to the inflation news text data. These procedures include actions like eliminating stop-words, numerical values, extra spaces, and performing word stemming, among others.

Subsequently, we apply the framework developed by Ardia *et al.* (2021) to compute a net sentiment index using our inflation news dataset. Although there are various methods for calculating sentiment, we opt for a lexicon-based approach, specifically employing a *valence-shifting bigrams* technique to compute the inflation sentiment index. The lexicon-based approach is generally regarded as transparent and computationally efficient when compared to alternative methods (Algaba *et al.*, 2020). Essentially, this approach involves matching words (or groups of words) in a document with a predefined list of *polarized* – positive or negative – terms, assigning numerical scores to each matched word based on its positive or

[8] Daily news items were obtained from online archives of *The Hindu Businessline, Economic Times, The Financial Express, The Mint and Business Standard.*

[9] Our inflation-related keyword set contains the following keywords: *consumer price index, inflation, headline inflation, food inflation, fuel inflation, core inflation, wholesale price index, wholesale prices, producer prices, consumer prices, retail prices.*

negative tone. For our analysis, we utilize the Loughran-McDonald (LM) lexicon, which is specifically designed for analyzing economic and financial texts (Loughran and McDonald, 2011). Our approach also captures the impact of *valence shifters* or keywords that may negate, amplify or de-amplify polarized words in the given document. Therefore, sentiment scores are adjusted for valence-shifting words depending on whether such words appear before the polarized keyword from the LM-lexicon. Note that, we perform the sentiment computation at the sentence-level to improve scoring efficacy before aggregating the net sentiment score to a desired frequency. The approach can be briefly described as follows:

1. Compute a net sentiment score $S_{i,n,t}$ for each *polarized* word i, in news item d_n published at time t using the LM-lexicon, such that *positive* and *negative* words are assigned a sentiment score of (+1) and (-1), respectively.

2. Adjust the score for *valence*-shifting words, if such words occur appear before the *polarized* word. This is achieved by multiplying the sentiment score by v_i, such that the score equals $v_i S_{i,n,t}$.

3. Aggregate net sentiment score at the document-level, such that $S_{n,t} = \frac{1}{w_d} \sum_{i=1}^{Q_d} v_i S_{i,n,t}$ where Q_d represents the total number of polarized words and w_d is the total number of words in each news article.

4. Finally, aggregate document-level score to obtain a time-series for net sentiment score (NSS) equaling $NSS_t = \frac{1}{F} \sum_{n=1}^{N_t} S_{n,t}$ where N_t is the total number of news articles of interest published on a given day t and F is the desired frequency ($F = 7$ for weekly; 30 for monthly, and so on.

The final inflation sentiment index for India is shown in Figure 2. Our sentiment index corresponds well with the overall headline inflation in the economy. While the sentiment index shares a strong, negative correlation with headline inflation, it also contains forward-looking information to predict inflation (see Figure 3 and Table 2). We, therefore, assume that a positive sentiment score indicates an anticipated fall in inflation, while a negative sentiment score is suggestive of an expected increase in inflation.

3.3 Preliminary Evidence on Anchoring of Inflation Expectations

One of the primary objectives of adopting an inflation targeting regime in many countries is to anchor long-run inflation expectations. We perform several preliminary checks to examine if the introduction of the new monetary policy regime has led to a change in the behavior of inflation expectations in India. We discuss two such preliminary enquiries below.

In the first set of analysis, we regress daily changes in 10-year government bond yields on inflation sentiment index, separately for the pre- and post-IT regime period. Yields on long-dated securities, in addition to expected short-term rates, also contain a term premium which can be directly influenced by the inflation outlook in the economy. If monetary policy is perceived to be credible and inflation expectations are well-anchored, inflation-related news should not affect long-term bond yields. Regression estimates for the pre- and post-IT period are presented in Table 3. The results suggest that while long-term bond yields responded to inflation-related news in the pre-IT period, it turned unresponsive after the adoption of the IT framework in India.

Similarly, for our second enquiry, we utilize inflation forecasts from the RBI's Survey of Professional Forecasters (SPF). The SPF survey provides us with measures of 1-quarter and 4-quarter ahead inflation forecasts, serving as indicators of short-run and long-run inflation expectations, respectively. We aim to determine if both short-run and long-run inflation expectations have altered their sensitivity to past inflation. If the anchoring hypothesis holds, a distinct difference in sensitivity for both expectations should be observable. The results, displayed in Table 4, reveal that professional forecasters surveyed by the RBI became insensitive to past realized inflation in the post-IT regime for 4-quarter forecasts. However, the sensitivity remained for 1-quarter ahead inflation forecasts, where forecasters adjusted their predictions in line with past inflation trends. Assuming that 4-quarter ahead forecasts represent long-term inflation expectations and 1-quarter ahead forecasts represent short-term expectations, these preliminary estimates suggest a shift in forecast adjustment behaviors with the introduction of the IT regime. This change affected long-term but not near-term expectations.

Despite the insights gained from Tables 3 and 4, we recognize the simplifying assumptions made in the above analyses. In particular, the measure of inflation expectations utilized above does not distinguish between short-run and long-run inflation expectations. A structured approach to measuring long-term expectations could involve assuming their persistence in the form of a random walk, as proposed by Stock and Watson (2007). Our use of median forecasts may not fully encapsulate the views of all forecasters in our sample. However, a limitation arises with the RBI's SPF data, as it does not offer individual forecasts. The Consensus Economics dataset mitigates this issue by providing monthly data for 14 individual forecasters. A comparison of median 1-year ahead inflation forecasts from this dataset with 4-quarter ahead median forecasts from SPF, as depicted in Figure 4, reveals a close tracking between the forecasts from the two datasets. In addition, beyond considering past inflation, we also incorporate other variables into the forecasters' information set by using an inflation sentiment index. This paper addresses these shortcomings by utilizing panel data on inflation expectations and examining the dynamic impact of a machine learning-based inflation sentiment index on short-run and long-run inflation expectations.

4 Decomposition of Inflation Forecasts into a Trend and a Cycle

4.1 Baseline Model

As described in the data section, our dataset consists of inflation forecasts for India from 14 different forecasters, covering the period from January 2010 to October 2022. Since these forecasters are all predicting the same variable and have access to similar information, it is reasonable to assume that these forecast series exhibit comparable long-term and medium-term characteristics. Our analysis of the stationarity of the deviations of each forecaster's inflation forecast from actual inflation in India reveals that these deviations are mean-reverting, suggesting long-term co-movement among the inflation forecasts of these 14 forecasters. Based on this evidence, we assume that these series share a common trend and cycle, and we employ state-space methods to extract these components. In other words, the inflation forecasts are cointegrated, and the long-run inflation expectation in our model represents the common stochastic trend across these forecasts.

The decomposition of inflation forecasts into a long-term persistent component and a short-term cyclical component builds upon the framework proposed by Stock and Watson (2007). However, our study extends and modifies this model by incorporating insights from the literature on the inflation gap, which models the difference between actual inflation and trend inflation as a cyclical component. This approach has been widely used in the literature on monetary policy credibility and forecasting, as seen in works by Cogley *et al.* (2010), Faust and Wright (2013) and Morley *et al.* (2015), among others.

Our model integrates key features of the forecast data by incorporating a common trend and cycle shared across all forecasters, while also accounting for a short-term idiosyncratic component unique to each forecaster's predictions. The multivariate model enhances the precision of our estimates for both the trend and cycle components.[10] Conceptually, our model identifies a common permanent shock through the long-term inflation expectation, a common temporary shock through the common cycle, and a forecaster-specific temporary shock through the idiosyncratic component.

With 14 forecasters providing 1-year-ahead inflation expectations in our analysis, we decompose each forecast into a trend, a cycle, and an idiosyncratic component. For clarity, we illustrate this approach using a model with three forecasters. This model can be easily extended for 14 forecasters. The observation equations for three forecasters are as follows:

$$\pi^1_{t,t+1} = \mu^1 + \tau_t + c_t + \eta^1_t \tag{1}$$

$$\pi^2_{t,t+1} = \mu^2 + \tau_t + \delta_2 c_t + \eta^2_t \tag{2}$$

$$\pi^3_{t,t+1} = \mu^3 + \tau_t + \delta_3 c_t + \eta^3_t \tag{3}$$

$\pi^i_{t,t+1}$ is 1-period ahead inflation expectations of forecaster i. μ^i captures the mean differences in inflation expectations. τ_t is common trend that follows a random walk with a drift. c_t is common cycle and δ_i are loadings on the cycle. The underlying assumption is that the common cycle loads differently for each forecaster. The structure of our model, which allows the loading on the cyclical component to vary across forecasters, acknowledges that while the underlying cyclical behavior may be common, its impact can differ depending on each forecaster's interpretation of economic conditions. This flexibility is crucial for capturing the differences in how forecasters perceive and respond to short-term fluctuations, while still maintaining the core assumption of a shared long-term trend. The idiosyncratic factors in the model also follow an AR(1) process, with shocks to these factors being jointly normally distributed with a mean of zero.[11]

[10] Effectiveness of the multivariate approach in a state-space setting has been demonstrated by various studies (Clark, 1989; Basistha and Nelson, 2007; Basistha and Startz, 2008; Chan *et al.*, 2018; Kishor and Koenig, 2022).

[11] This framework does not account for the potential co-movement between these inflation forecasts and global inflation forecasts. To explore this, we conducted a preliminary analysis of the median 1-year-ahead inflation expectations from five inflation-targeting countries: Australia, New Zealand, Brazil, Chile, Colombia, and India. We found no evidence of long-run co-movement among these inflation expectations, as the null hypothesis of no cointegration could not be rejected for these time series. Similarly, when we examined the 1-year-ahead inflation forecasts for four emerging market inflation targeters- Brazil, Chile, Colombia and India—we again found no evidence of co-movement. This lack of synchronization aligns with our earlier findings, which show that India's inflation dynamics are not in sync with those of other inflation-targeting

The corresponding transition equations included in the model are:

$$\tau_t = \mu^\tau + \tau_{t-1} + u_t^\tau, u_t^\tau \sim iidN(0, \sigma_\tau^2) \tag{4}$$

$$c_t = \beta c_{t-1} + u_t^c, u_t^c \sim iidN(0, \sigma_c^2) \tag{5}$$

$$\eta_t^i = \phi_i \eta_{t-1}^i + \epsilon_t^i, u_t^c \sim iidN(0, \sigma_i^2) \tag{6}$$

In matrix form, the observation equation can be written as:

$$\begin{bmatrix} \pi_{t,t+1}^1 \\ \pi_{t,t+1}^2 \\ \pi_{t,t+1}^3 \end{bmatrix} = \begin{bmatrix} \mu^1 \\ \mu^2 \\ \mu^3 \end{bmatrix} + \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 1 & \delta_2 & 0 & 1 & 0 \\ 1 & \delta_3 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \tau_t \\ c_t \\ \eta_t^1 \\ \eta_t^2 \\ \eta_t^3 \end{bmatrix} \tag{7}$$

The transition equation has the following representation:

$$\begin{bmatrix} \tau_t \\ c_t \\ \eta_t^1 \\ \eta_t^2 \\ \eta_t^3 \end{bmatrix} = \begin{bmatrix} \mu^\tau \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & \beta & 0 & 0 & 0 \\ 0 & 0 & \phi_1 & 0 & 0 \\ 0 & 0 & 0 & \phi_2 & 0 \\ 0 & 0 & 0 & 0 & \phi_3 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ \eta_{t-1}^1 \\ \eta_{t-1}^2 \\ \eta_{t-1}^3 \end{bmatrix} + \begin{bmatrix} u_t^\tau \\ u_t^c \\ \epsilon_t^1 \\ \epsilon_t^2 \\ \epsilon_t^3 \end{bmatrix} \tag{8}$$

The transition-equation error terms are joint-normally distributed with mean zero. The above set of observation and transition equations constitute our "baseline" model. The full model can be put into state-space form and estimated using maximum likelihood via the Kalman filter.[12]

The estimated hyperparameters for this model are shown in Table 5. There are a total of 58 parameters in our model: 14 intercepts, 15 AR parameters, 16 standard errors, and 13 loading parameters. P-values are reported in parentheses. Several interesting observations can be made from these estimates, particularly regarding the relative importance of shocks to trends and cycles. The loadings on the common cycles are positive for most of the forecasters, implying positive co-movement in the cycles even without imposing any restrictions on these loadings. In our model, the loading on the common cyclical component for the first forecaster, δ_1, is normalized to one. This normalization is a standard approach in this class of models,

countries, whether developed or emerging.

[12]For the details on the estimation procedure, see Chapter 2 of Kim and Nelson (2000).

where either the variance of the common shock (the cyclical component) or the loading of one series on the common component must be fixed to one for identification purposes.[13] In our case, we chose to normalize the loading for the first forecaster to one, meaning that this forecaster's inflation forecast is fully influenced by the common cyclical component without any rescaling.This normalization allows us to identify the model by fixing one parameter, thereby avoiding issues of under-identification that could arise if all parameters were allowed to vary freely. The remaining forecasters have different loadings δ_i, which reflect how much their inflation forecasts are influenced by the common cyclical component relative to the first forecaster. For instance, a loading of 0.05 for forecasters 3 and 4 indicates that their forecasts are only minimally affected by the common cycle, while a loading of 1.56 for forecaster 10 suggests a much stronger influence. [14]

The persistence parameter for the common cycle is 0.93, implying a half-life of around 7 months. For most forecasters, the standard errors of the idiosyncratic factors are higher than the volatility of the trend and the common cycle. The intercepts capture the mean differences in the inflation forecasts of different forecasters. The estimates from the model also suggest that we do not suffer from the pile-up problem, which is commonly associated with insignificant standard errors in unobserved component models.[15].

As explained earlier, the inflation trend in our model is the persistent or long-term component of inflation that filters out short-term fluctuations. This trend is often equated with the long-run inflation expectations of economic agents since it represents their beliefs about the underlying inflationary pressures that will persist over time. In our exercise, trend inflation in the UC model is assumed to capture the long-run inflation expectation of the private sector forecasters. The estimated inflation trend and cycle from this UC model are shown in Figure 5.

At the beginning of this period, in January 2010, long-run inflation expectations stood at a relatively high level of 7.57 percent. Long-run expectations remained elevated during the subsequent years as they were affected by high and volatile inflation during 2010-13. Overtime, we observe a gradual but consistent decline in these expectations. By December 2014, they had dropped to 6.80 percent. This downward trend persisted, suggesting that the markets were becoming increasingly confident in the effectiveness of the measures taken to combat inflation and stimulate economic growth. Around mid-2015, long-run in-

[13]See Stock and Watson (2016) for excellent discussion on identification issue in these class of models.

[14]We also re-estimate the model by normalizing the loading on another forecaster, and the results remain robust.

[15]See Stock and Watson (1998).

flation expectations began to plateau and stabilize at a level of around 5.5 to 6 percent. This steadying of expectations indicated that the private forecasters had developed a more consistent outlook for the long-term inflationary environment. This coincided broadly with an agreement in February 2015 between the RBI and the government formalized the new IT approach. For 4-5 years, long-run inflation expectations as measured by inflation trend, remained low and stable. As we moved into 2020, we encountered a new set of challenges in the form of the COVID-19 pandemic.

The unprecedented economic disruption caused by the pandemic led to a surge in uncertainty, and we saw a temporary increase in long-run inflation expectations. This increase, however, was relatively short-lived, and expectations quickly returned to their pre-pandemic range. By October 2022, the long-run inflation expectations had settled at around 6.22 percent. This level, while still above pre-financial crisis levels, reflects a degree of stability and confidence in the economic outlook. The stabilization of long-term inflation expectation in the later part of the sample also coincided with the collapse of global oil prices in 2014. One could argue that the decline in long-term inflation expectation reflected the decline in oil prices. Chinoy et al. (2016) have specifically examined this issue and found limited role of global factor in disinflation in India during this time period. A key reason for the limited pass-through of global oil prices to domestic inflation is that the retail price for many petroleum products in India was subsidized before oil prices fell, and much of the price decline was captured by the government through tax increases. For example, between October 2014 and March 2016, crude oil prices fell by 56%, yet retail prices of gasoline and diesel only declined by 13% and 21%, respectively. This explains why global factors, particularly oil prices, played a relatively minor role in shaping inflation expectations in India during our study period.

We also observe similar pattern for inflation cycle as shown in the *bottom panel* of Figure 5. The inflation cycle prior to 2016-17 was higher on average as reflected in the higher actual inflation expectations. One could argue that it was influenced by a combination of domestic and global economic factors. However, post-2017, a marked change occurred as inflation cycle turned consistently negative, implying the inflation forecasts were lower than trend. This is not surprising since by construction inflation trend adjusts slowly and inflation forecasts adjusted much more quickly than the inflation trend. In the section below we examine how these long-run inflation expectations as measured by trend and short-run inflation expectations as measured by common cycle respond to inflation sentiment in the newspapers.

4.2 Break in the Variance of Common Trend and Common Cycle

In this section, we introduce a modification to the baseline model by allowing for a break in the variance of the common trend and common cycle components. One could argue that the introduction of IT may have altered the nature of shocks affecting the common trend and common cycles in our baseline model. Incorporating this break into the model allows us to potentially better capture the dynamic changes in inflation expectations that may have occurred as a result of the IT regime. Specifically, we allow for a change in the variance of the shocks to the common trend (σ^2_τ) and common cycle (σ^2_c) components from the period before and after the adoption of IT.

To operationalize this, we introduce a binary indicator variable D_t, which takes the value 0 before the adoption of IT (pre-IT) and 1 afterward (post-IT). The variance of the common trend and common cycle components is then allowed to vary according to this indicator, as shown in the modified transition equations:

$$\tau_t = \mu^\tau + \tau_{t-1} + u^\tau_t, \quad u^\tau_t \sim i.i.d.\ N(0, \sigma^2_{\tau,pre} \cdot (1 - D_t) + \sigma^2_{\tau,post} \cdot D_t) \tag{9}$$

$$c_t = \beta c_{t-1} + u^c_t, \quad u^c_t \sim i.i.d.\ N(0, \sigma^2_{c,pre} \cdot (1 - D_t) + \sigma^2_{c,post} \cdot D_t) \tag{10}$$

In these equations, $\sigma^2_{\tau,pre}$ and $\sigma^2_{c,pre}$ represent the variances of the common trend and common cycle before the adoption of IT, while $\sigma^2_{\tau,post}$ and $\sigma^2_{c,post}$ represent the variances after IT adoption. By allowing for a shift in these variances, we can more accurately capture the potential changes in inflation dynamics due to the policy shift.

All other features of the model, including the common trend and cycle components, the idiosyncratic noise terms, and the estimation method using state-space techniques, remain the same as described in the baseline model. The only modification is the introduction of a break in the variance of the common components.

The robustness of our results is demonstrated through a comparison of the baseline and break-adjusted decompositions of inflation expectations into their common trend and cycle components. The graphs of the common trend and common cycle, are shown in Figure 6, indicate that allowing for a break in both the trend and cycle does not significantly alter the results.[16] The trend comparison graph shows that the two series, representing the baseline and break-adjusted trends, remain closely aligned, suggesting that the long-

[16] The estimated parameters along with their standard errors from this model are reported in Appendix A.2. The results are very similar to the baseline model.

term inflation expectations are stable regardless of the potential structural break. Similarly, the cycle comparison graph illustrates that the cyclical component of inflation expectations remains consistent between the baseline and break-adjusted models. One of the implications of allowing the break in the variances in two regimes is that we observe smaller cyclical component in the post-IT period. Although it is lower in magnitude, the overall variation is very similar to our baseline model.

5 Impact of Inflation Sentiment Shock on Inflation Expectations

Examining the impact of incoming news about inflation on inflation expectations provides us with a way to infer the effectiveness of the IT regime. We do so by using the local projections (LP) framework of Jordà (2005).[17] In particular, we adopt the state-dependent local projections that have been applied by Ramey and Zubairy (2018). As an illustration, a simple, linear LP model can be specified as follows:

$$y_{t+h} = \alpha_h + \beta_h \cdot shock_t + \gamma \cdot \varkappa_t + \varepsilon_{t+h} | h = 1, 2, ...H \tag{11}$$

where y_t is the response variable of interest, $shock_t$ is an identified shock variable, $\varkappa_t$ is a set of exogenous and/or pre-determined control variables and h is the forecast horizon. While α_h denotes the regression constant, coefficient β_h corresponds to the response of y at time $t+h$ to the shock variable i.e., s at time t. The impulse responses are the set of estimated β_h coefficients. The linear local projection model can be easily extended to account for state-dependence as follows:

$$y_{t+h} = \alpha_h + \delta_r \cdot \{\beta_h^{R1} \cdot shock_t\} + (1 - \delta_r) \cdot \{\beta_h^{R2} \cdot shock_t\} + \gamma \cdot \varkappa_t + \varepsilon_{t+h} | h = 1, 2, ...H \tag{12}$$

which corresponds to two distinct regimes $R1$ and $R2$. In our case, the response variable y_t is the long-run (trend) or short-run (cycle) inflation expectations. Set $\varkappa_t$ consists of upto 12 lags of y along with one-period lagged values of Index of Industrial Production (IIP, YoY%), headline consumer price inflation (CPI-C, YoY%), nominal brent crude oil price (Oil, YoY%) and weighted average call money rate (WACR, YoY%) to control for economic activity, supply shocks and the stance of monetary policy. Data was obtained from publicly

[17] Refer to Jordà (2023) for an excellent review of the local projections approach.

available data sources, namely *Database on Indian Economy* (DBIE) maintained by the RBI. The first official meeting of the MPC in India took place during October 2016. We choose this date for regime switch to inflation targeting in India. Therefore, δ is a binary variable that equals 1 (one) after October 2016 (and 0 otherwise). Consequently, β_h^{R1} and β_h^{R2} are state-dependent coefficients for pre-IT and post-IT regimes. The model defined in equation (13) is estimated using standard ordinary least squares (OLS) method with robust standard errors (Newey and West, 1987).

We trace the impact of a shock to the inflation sentiment index on long-horizon and short-horizon inflation expectations, as measured by the trend and cycles estimated in our baseline model, in the pre- and post-IT regime. Credibility of monetary policy can be inferred by how the response of inflation expectations has changed over time. We measure the inflation sentiment shock as a residual from an AR(1) regression of the inflation sentiment index.[18] The results from the local projection analysis are shown in Figure 7.

The *top panel* in Figure 7 illustrates the impact of an inflation sentiment shock on long-run inflation expectations, as measured by inflation trend, in the pre- and post-IT regime. There is clear evidence of a regime shift in the results, with long-run inflation expectations responding differently in different regimes. Trend inflation responded significantly to inflation sentiment in the pre-IT period, and this effect was persistent and peaked around 16-18 months. This response became insignificant in the post-IT regime, remaining insignificant for most forecast horizons. If we follow Bernanke (2003)'s hypothesis that a credible monetary policy leads to long-run inflation expectations becoming insensitive to news about inflation, then there is strong evidence that the adoption of the IT regime in India led to a more credible monetary policy.

This is also reflected in the results plotted in the *bottom panel* of Figure 7, where we trace out the dynamic impact of an inflation sentiment shock on the cycle of inflation forecasts that capture short-run inflation expectations. Unlike a regime change in the responsiveness of long-run inflation expectations, we do not observe a change in the responsiveness of short-run inflation expectations to an inflation sentiment shock across the two monetary policy regimes. Professional forecasters' transitory component of inflation forecasts does not respond to changes in inflation sentiment for most forecast horizons, and the introduction of

[18] One could argue that the inflation sentiment index also reflects the views of individual forecasters, as they regularly provide their views to the news media. Our residual-based approach to calculating shocks only measures the unsystematic component of sentiment. Since the method for calculating the index remains consistent throughout the entire sample period, our shock at time t should solely capture the unanticipated component that was not available to professional forecasters at the time the forecasts were made.

a new monetary policy regime in 2016 has not led to a change in the way those expectations respond to these shocks. These results are robust to the inclusion of different controls.

We also use the trend and cycle estimated from the model with break in trend and cycle variances and perform state-dependent local projection analysis. The results are shown in Figure 9. The analysis shows that the estimated responses of both long-run and short-run inflation expectations to inflation sentiment shock remain consistent, even when allowing for a break in the common trend and cycle. The impulse responses derived from the break-adjusted model closely align with those from the baseline model, indicating that the introduction of a structural break does not significantly alter the trajectory or magnitude of the responses. This stability in the local projection results reinforces the reliability of our findings, suggesting that the anchoring of long-term inflation expectations under the IT regime remains robust to potential structural changes in the data.

6 Robustness Check

6.1 Inclusion of Global Controls in Local Projection Analysis

In addition to the baseline analysis, we expanded the local projection IRF analysis by including additional global controls, specifically consumer price inflation for G7 countries (sourced from the OECD) as well as the world commodity price index (YoY%) and the world food price index (YoY%) sourced from IMF. The results, now presented in Figure 8, remain qualitatively consistent with the earlier findings. The significant U-shaped response of long-run inflation expectations to an inflation sentiment shock during the pre-IT period persists, reinforcing the notion that long-run inflation expectations were more sensitive to inflation sentiment before the adoption of the IT regime. Importantly, by controlling for these global price measures, we can be more confident that the observed dynamics are not driven by global inflationary pressures but are instead a reflection of domestic monetary policy shifts. Despite the inclusion of these global controls, the pre-IT regime continues to show a persistent and peaked response around 16-18 months, while the post-IT regime maintains its insignificance across most forecast horizons.

We also perform the state-dependent IRF analysis for model with breaks in variances of long-term and short-term inflation expectations and the results are robust to the inclusion of global controls.[19] These results show that even with the addition of global controls, the core

[19] We do not report these results here for brevity but are available upon request.

dynamics remain unchanged and the inflation expectations response we observe is insensitive to global factors.

6.2 A Dynamic Factor Model with Stochastic Volatility

Another method that can be applied to decompose inflation forecasts of these professional forecasters is a dynamic factor model with stochastic volatility. A factor model decomposes the movements in variables into those attributed to latent factors and idiosyncratic factors. Standard factor models do not attempt to model the dynamics of volatility and typically assume that the variance-covariance matrix is constant. Empirical evidence suggests that multivariate factor stochastic volatility models offer a promising approach to modeling multivariate time-varying volatility.

The multi-factor stochastic volatility model we use is based on Kastner *et al.* (2017). Specifically, the model is given by:

$$\mathbf{y}_t = \Lambda \cdot f_t + \Sigma_t^{\frac{1}{2}} \varepsilon_t, \varepsilon_t \sim N_m(0, I_m) \tag{13}$$

$$f_t = V_t^{\frac{1}{2}} u_t, u_t \sim N_r(0, I_r) \tag{14}$$

where $\mathbf{y}t = (y_{1t}, \ldots, y_{mt})'$ is a zero-mean vector of $m = 14$ one-step-ahead inflation forecasts from professional forecasters, with these forecasts demeaned to have mean zero; $\mathbf{f}_t = (f_{1t}, \ldots, f_{rt})'$ is a vector of r unobserved latent factors; $\Sigma_t = \text{Diag}(\exp(h_{1t}), \ldots, \exp(h_{mt}))$ and $V_t = \text{Diag}(\exp(h_{m+1,t}), \ldots, \exp(h_{m+r,t}))$ are diagonal matrices; and Λ is an unknown $m \times r$ matrix with elements Λ_{ij}. Furthermore, the latent factors and idiosyncratic factors can each follow distinct stochastic volatility processes:

$$h_{it} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \sigma_i \eta_{it}, \quad i = 1, \ldots, m + r \tag{15}$$

where $\eta_{it} \sim \mathcal{N}(0, 1)$ and $h_{i0}|\mu_i, \phi_i, \sigma_i \sim \mathcal{N}(\mu_i, \sigma_i^2/(1 - \phi_i^2))$.

The number of factors r is determined by comparing cumulative log predictive Bayes factors. Specifically, we calculate one-day-ahead predictive likelihoods for models with varying numbers of factors, ranging from zero to 4. These predictive likelihoods are then accumulated over time to produce cumulative log predictive Bayes factors. The model with the highest cumulative log predictive Bayes factor is considered the best-performing and is therefore preferred for capturing the underlying structure in the data. Additionally, we examine the plot of log predictive Bayes factors against the number of factors, which can be used similarly to a scree plot in principal component analysis to determine the appropriate number of factors. In our example, this approach selects $r = 2$ factors.

In the multi-factor stochastic volatility model, time-varying volatility can induce autocorrelation in the factors. The ability to model this autocorrelation through time-varying volatility allows this class of model to capture both the changing uncertainty and the clustering of economic effects over time, making the model particularly well-suited for inflation that exhibits these features. Due to its large scale, this model is commonly estimated using a Bayesian Markov Chain Monte Carlo (MCMC) estimation algorithm. Although Bayesian MCMC estimation is highly efficient, it poses a significant computational challenge when dealing with a moderate to large number of variables. To address this issue, Kastner *et al.* (2017) introduce an innovative approach that bypasses the traditional forward-filtering backward sampling algorithm. Instead, they adopt a "sampling all without a loop" strategy, explore various reparameterizations, including partial non-centering, and implement an ancillary-sufficiency interweaving strategy to enhance MCMC estimation at the univariate level. This methodology can be directly applied to estimate heteroscedasticity in latent variables like factors.[20] To generate stochastic volatility draws, this model relies on an approximation method developed by Kim *et al.* (1998), which has demonstrated strong performance and widespread usage in recent literature, as evidenced by Stock and Watson (2007, 2016) and Primiceri (2005). Lastly, since the means of factors lack separate identifiability, we adhere to established literature practice and adjust the series by demeaning them before estimation.

We illustrate the estimated median inflation trend and cycle derived from this approach in Figure 10. As depicted in the plot, both of these graphs closely resemble those obtained in the previous section when we employed a common trend and common cycle representation. It is important to note that we can compare the direction of the two plots but not the specific levels, as inflation forecast values have been standardized in the current model. Over the sample period, long-term inflation expectations in India initially began at a high level and gradually declined. Around 2015, these expectations began to stabilize, reflecting a consistent outlook among private forecasters. The advent of the COVID-19 pandemic briefly led to an increase in long-term inflation expectations. A similar pattern emerges in the inflation cycle, with a notable shift towards consistently lower inflation forecasts relative to the trend after 2017, indicating a heightened sensitivity to evolving economic conditions.[21]

[20] For a comprehensive understanding of the estimation process, readers are referred to Kastner *et al.* (2017) and Hosszejni and Kastner (2020).

[21] The estimated median factor loadings for both factors are reported in Appendix A. The loadings on the

We use the trend and cycle estimated from this model to examine the impact of an inflation sentiment shock on long-term and short-term inflation expectations in the pre-IT and post-IT regimes. The results are presented in Figure 11. The analysis demonstrates that the estimated responses of both long-term and short-term inflation expectations to an inflation sentiment shock remain consistent with our baseline model. The robustness of the local projection results reinforces the reliability of our findings, suggesting that the anchoring of long-term inflation expectations under the IT regime remains stable, even when accounting for potential changes in the model specification used to estimate long-term and short-term inflation expectations.

6.3 Univariate Model for Median SPF Forecasts with Extended Data

In this subsection, we apply the univariate version of the trend-cycle decomposition model to another survey, the Survey of Professional Forecasters (SPF), conducted by the Reserve Bank of India, the details of which are presented in the data description section. The SPF dataset offers the advantage of providing an additional two years of data compared to our previous analysis. While the baseline model's sample starts in 2010, this univariate model begins in 2008, allowing us to capture the dynamics of inflation expectations for a couple of years before 2010. The model structure remains consistent with the earlier baseline model but is adapted to handle the quarterly frequency of the median SPF forecasts.

Adding these two additional years potentially provides a more comprehensive view of inflation expectations, particularly at the beginning of the sample period, though it comes at the cost of using quarterly rather than monthly data. The model parameters are estimated using maximum likelihood methods via the Kalman filter, following similar procedures used in previous sections.

One challenge in decomposing a univariate series is the difficulty in distinguishing between the trend and cycle. We encountered this issue during estimation, as convergence was difficult to achieve in the maximum likelihood estimation, complicating the identification of these components in our context. Specifically, we faced difficulties in estimating the standard

first factor (trend) are positive for all forecasters, whereas the corresponding estimate for the cyclical factor is smaller and, in some cases, negative. Despite the differences in modeling structures and identification schemes, the fact that the factor model identifies two factors, and the loadings on the estimated median trend are consistently positive and close to one, demonstrates the robustness of the models presented in this paper.

errors of the parameters.[22] Unlike in our baseline model, where we leverage information from multiple forecasters and long-run comovement in forecasts to extract a measure of the trend, the univariate framework lacks this advantage. The common trend and common cycle model captures the shocks that are shared across all the forecasters, allowing us to resolve the identification problem. Nevertheless, we compare the estimated trend and cycle components derived from the point estimates of the baseline UC model with the standard univariate UC model of Stock and Watson (2007), which includes stochastic volatility, in Appendix B. The results suggest that both univariate models exhibit similar properties, with the trend closely mimicking the median forecast and only a small variation being captured by the cyclical component.

6.4 Deviation of Long-term Inflation Expectations from Inflation Target

We have shown that after adopting Inflation Targeting (IT), long-run inflation expectations became less responsive to inflation news. However, we haven't yet explored the extent of deviation from the 4 percent official target in the post-IT era. Figure 12 illustrates this deviation. Following India's implementation of IT in 2016, with a 4 percent target, there was a significant period where long-run inflation expectations gradually aligned with this target. This trend is evident in the data from 2016 to 2020. Recently, however, there's been an increase in long-term inflation expectations, indicating a divergence from the 4 percent target. We conducted a Quandt-Andrews structural breakpoint test to formally analyze this deviation. A structural break was identified in August 2020, aligning with the deviation plot. Table 6 presents the regression coefficients for the entire dataset and subsets divided by the August 2020 breakpoint. Before 2020, the Wald Test showed no significant difference from zero in the unconditional mean. Around August 2020, a notable change occurred: the intercept rose to 1.36, and the unconditional mean of this deviation significantly differed from zero. Addressing this divergence is vital for the Reserve Bank of India (RBI) to maintain the effectiveness of the IT framework. Prolonged divergence could undermine the IT regime's credibility in India. A more detailed analysis of inflation expectations' sensitivity is needed but is limited by the small post-2020 sample size.

[22] There is a rich literature in econometrics on this identification problem. See Stock and Watson (1998) for details.

7 Conclusions

This paper examines the impact of inflation targeting (IT) on inflation expectations in India, focusing on the period from January 2010 to October 2022. The adoption of IT by the Reserve Bank of India (RBI) in 2016 marked a significant shift in India's monetary policy framework, aligning it with global best practices. Our research shows that this policy shift has played a crucial role in anchoring long-term inflation expectations, a key objective of the IT regime.

This study employs a multivariate unobserved components model that leverages data from multiple forecasters to disentangle the common long-term trend from short-term fluctuations. Additionally, we introduce a novel inflation sentiment index, constructed using advanced text-mining techniques applied to a dataset of news articles from leading business newspapers in India. Using a state-dependent local projection approach, we examine the impacts of inflation-related news on both long-term and short-term inflation expectations. Our findings indicate that prior to the adoption of IT, long-term inflation expectations in India were highly sensitive to inflation sentiment, reflecting a susceptibility to economic news and developments. However, post-IT, we observe a marked decrease in this sensitivity, suggesting that the RBI's commitment to its inflation target has strengthened the credibility of its monetary policy. These results offer valuable insights into the transmission of monetary policy in a large and diverse emerging market like India.

Future research could extend our approach to other inflation targeting countries, particularly those in emerging markets, to provide a comparative perspective on the effectiveness of IT regimes. However, it's important to note that India's economy is largely domestically driven and vast in scale, which may influence the applicability of these findings to other contexts. Our approach can be applied to other countries where data on professional forecasters and newspaper articles are available, enabling similar analyses of inflation expectations and sentiment. By extending this methodology to different economic contexts, future research can further explore the effectiveness of inflation targeting across various economies, providing a more comprehensive understanding of how monetary policy frameworks function in different settings. This would not only enhance the generalizability of our findings but also offer valuable policy insights for central banks globally, while taking into account the unique characteristics of each economy, such as its size and degree of domestic orientation.

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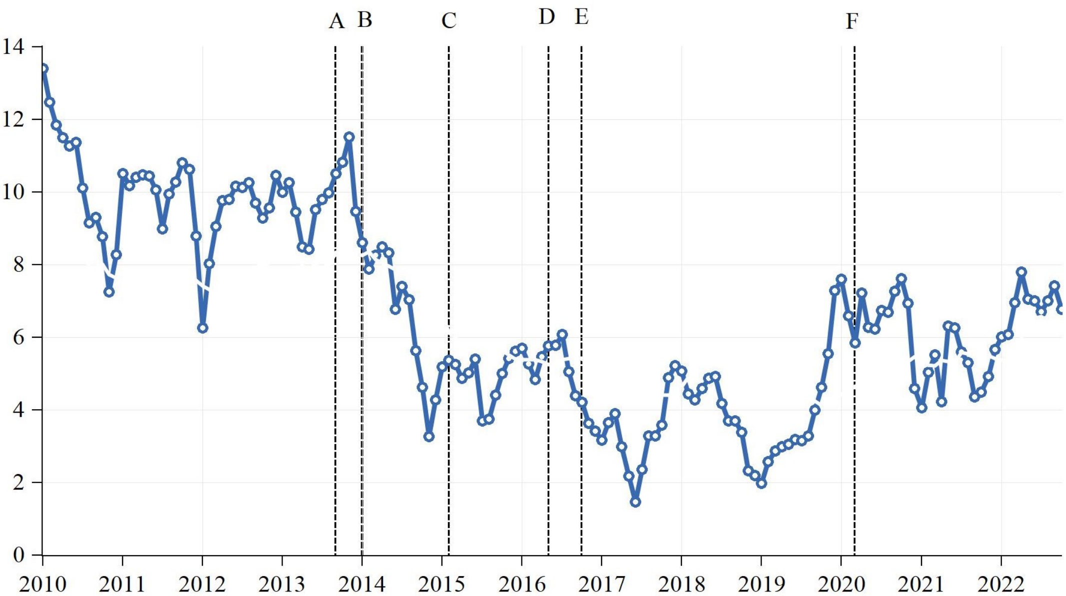
Figures and Tables

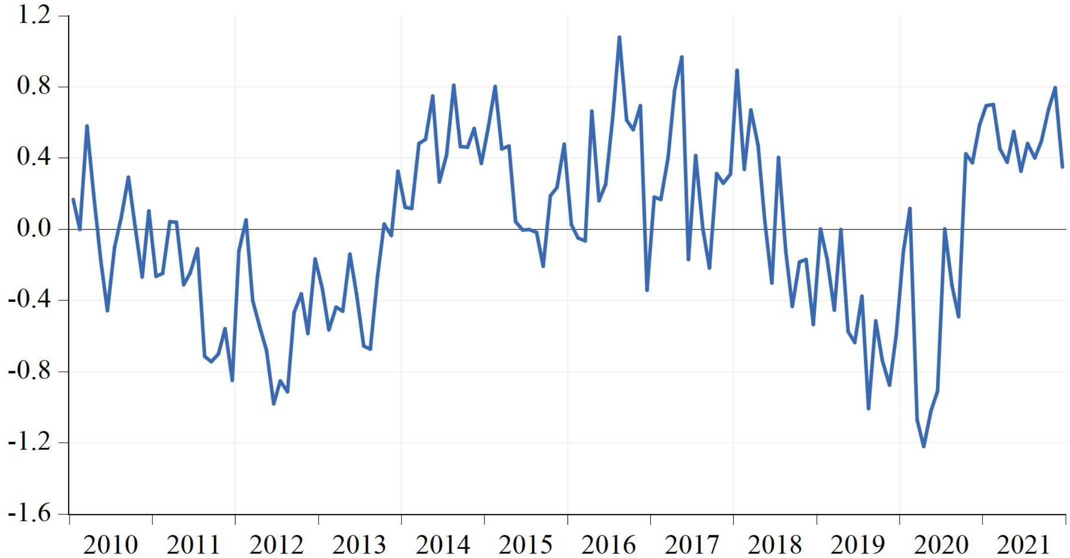
Figures

Figure 1: India's Transition to Flexible Inflation Targeting (FIT) Regime



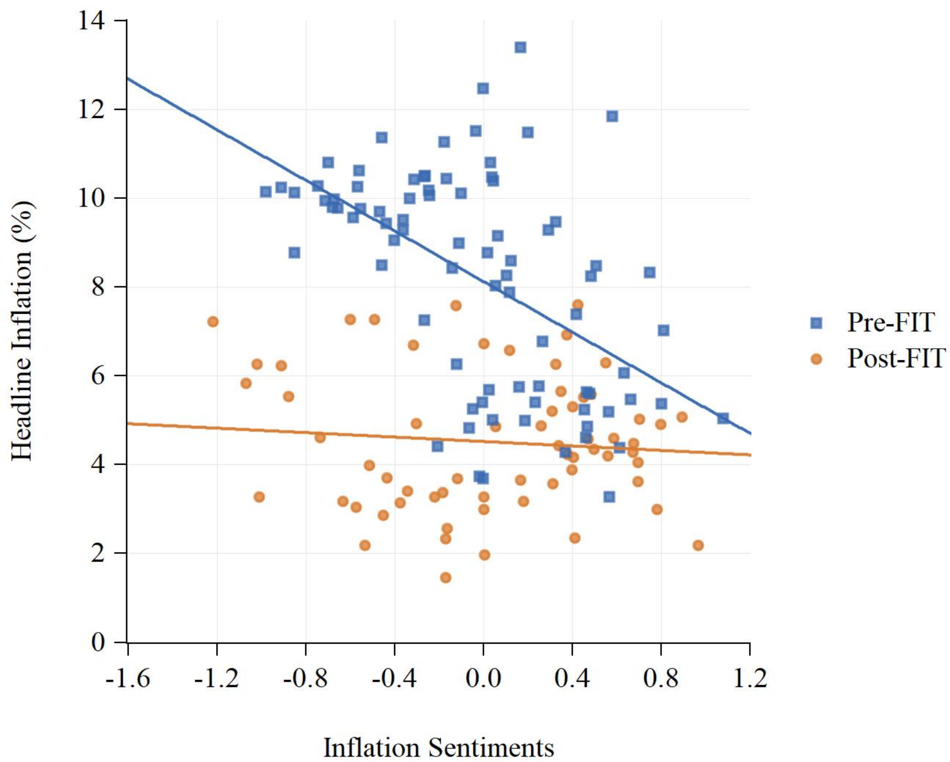
Note: The above figure highlights India's transition to the FIT regime during the 2013-2016 period. The solid blue line shows the headline inflation measured using the official consumer price index-combined (CPI-C). The vertical lines correspond to milestone events in the adoption of the FIT framework: (A) Dr. Raghuram Rajan takes over as RBI Governor in September 2013; (B) Expert Committee chaired by Dr. Urjit Patel, Deputy Governor, RBI recommends the adoption of FIT in January 2014; (C) Agreement to adopt new Monetary Policy Framework Agreement signed between the Central Bank and Government of India in February 2015; (D) The RBI Act of 1934 was amended to legally sanction FIT framework in May 2016; (E) First meeting of the newly constituted six-member Monetary Policy Committee (MPC) held in October 2016; (E) Outbreak of the Covid-19 Pandemic.
Source: Reserve Bank of India (RBI).

Figure 2: Newspaper-based Inflation Sentiment Index for India



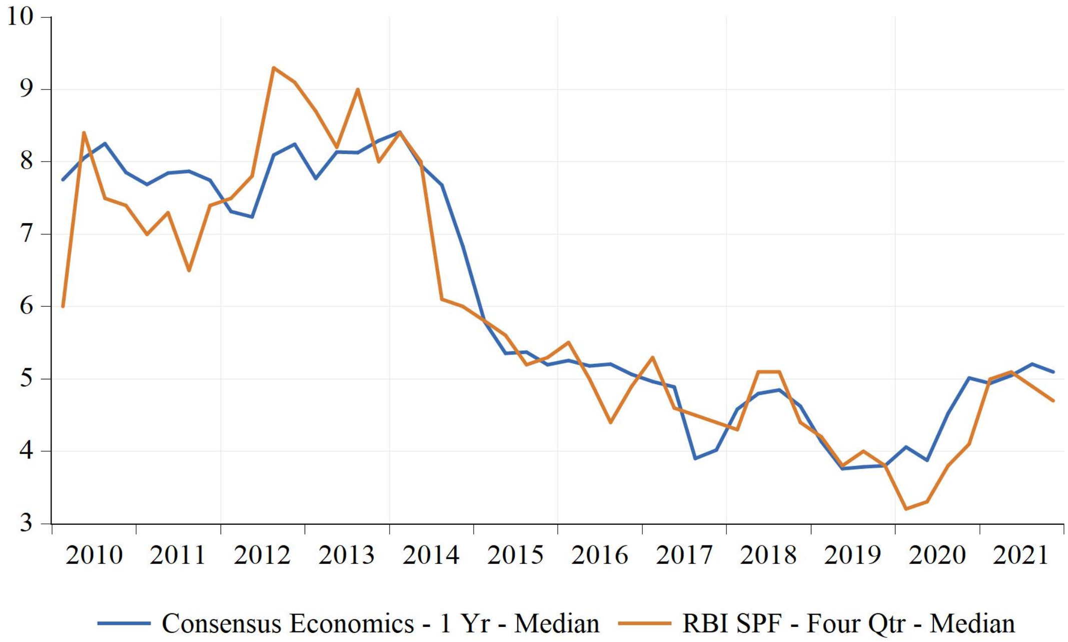
Note: The above figure shows the news-based inflation sentiment index for India. The index was constructed by applying natural language processing (NLP) techniques on daily inflation-related news articles published in leading business news dailies in India. The index measures the net sentiments around ”inflation” as captured in news articles, such that, positive (negative) values of the index underline a positive (negative) sentiment around consumer price inflation.
Source: Authors' estimates.

Figure 3: Headline Inflation and News-based Inflation Sentiment Index: Correlation across pre- and post-FIT



Note: The above figure shows the correlation between headline inflation and our news-based inflation sentiment index for India across the pre-FIT period (2010M01:2016M09) and post-FIT period (2016M10:2022:M10). Headline inflation for India, measured as the year-on-year growth in consumer price index (CPI), is plotted on the vertical axis, whereas the net inflation sentiments index is plotted on the horizontal axis. The solid blue and orange line depict the *line of best fit* across the pre- and post-FIT regime, respectively.
Source: Authors' estimates.

Figure 4: Comparison of One-year ahead Inflation Forecasts

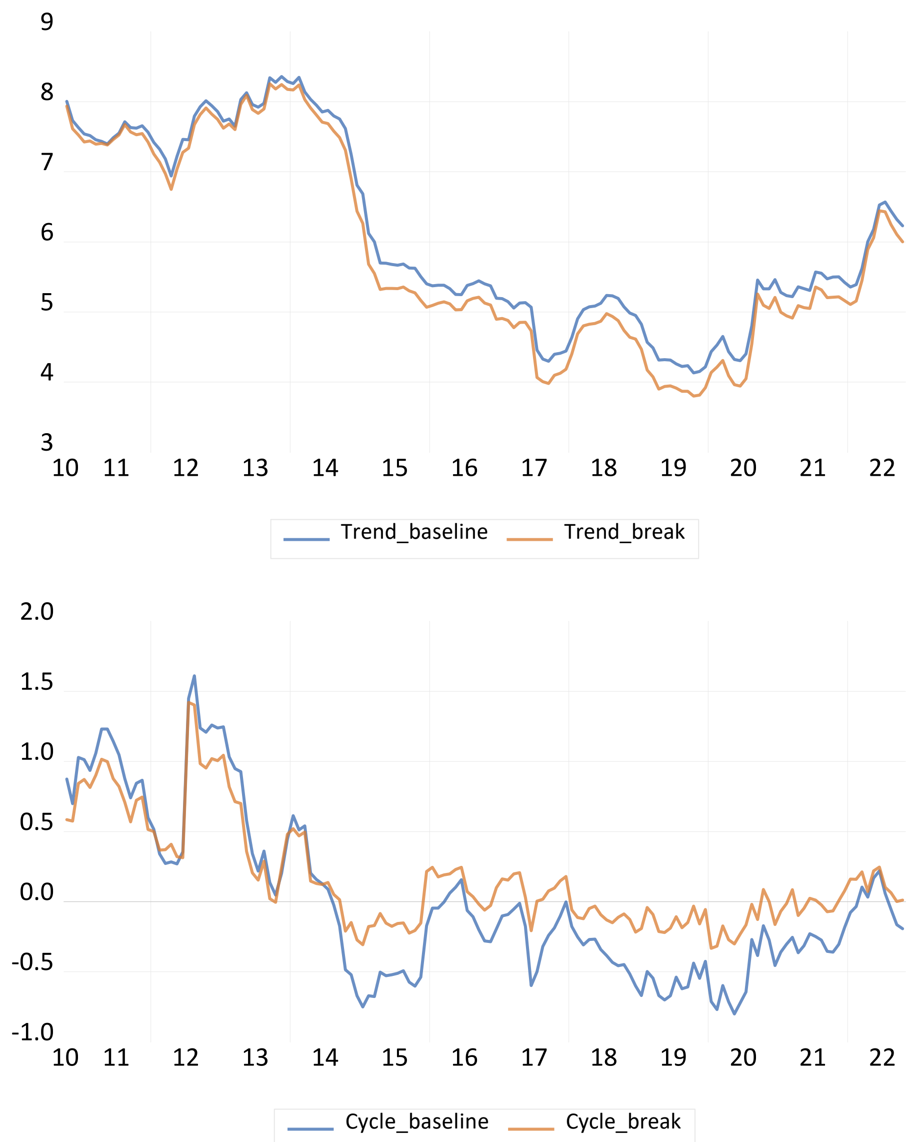


Note: The above figure compares one-year ahead inflation expectations derived from *Consensus Economics* and RBI's *Survey of Professional Forecasters* (SPF) shown using solid *blue* and *orange* line, respectively. Both surveys capture the inflation expectations of professional forecasters.
Source: Authors' estimates.

Figure 5: Long-run (trend) and Short-run (cycle) Inflation Expectations from the Baseline Unobserved Component (UC) Model

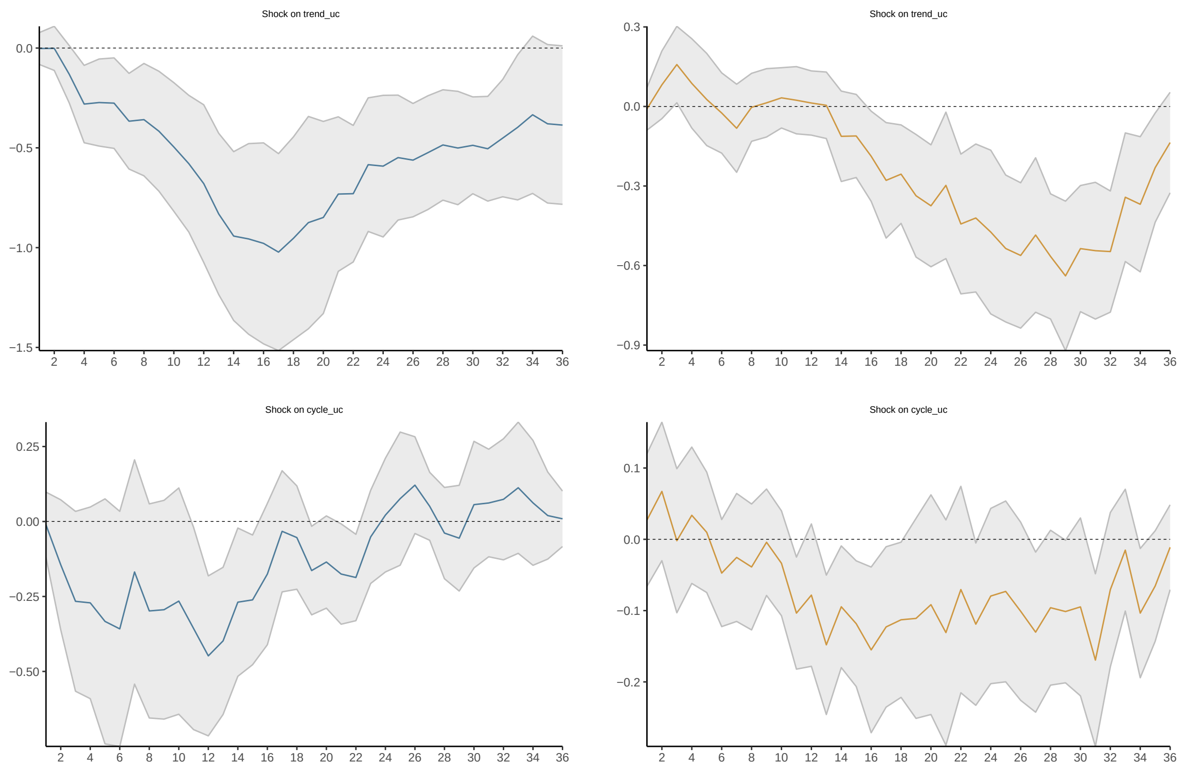
Note: The above figure plots the long-run (trend) and short-run (cycle) inflation expectations derived from our baseline *unobserved components* model described in section 4. The top panel plots the trend component while the bottom panel plots the cyclical component of one-year ahead inflation expectations for India.
Source: Authors' estimates.

Figure 6: Comparison with Model with Break in Variances



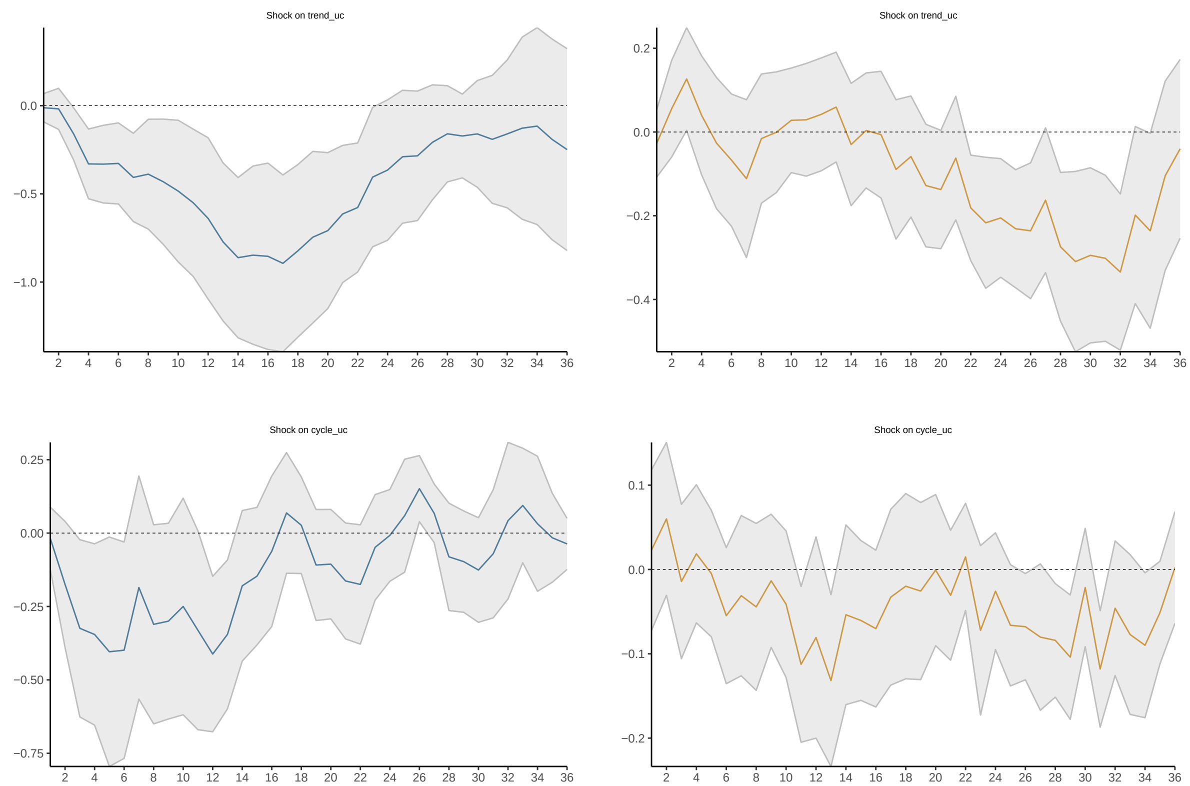
Note: The above figure compares the long-run (trend) and short-run (cycle) inflation expectations derived from our baseline UC model with corresponding estimates from the model with break in variance as described in 4.2. The *top panel* shows the long-run (trend) expectations whereas the *bottom panel* shows the short-run (cycle) expectations from the baseline model (shown in solid blue line) and the model with variance break (solid yellow line).
Source: Authors' estimates.

Figure 7: State-dependent Impulse Responses of Inflation Expectations to Inflation Sentiment Shock (Baseline UC Model)



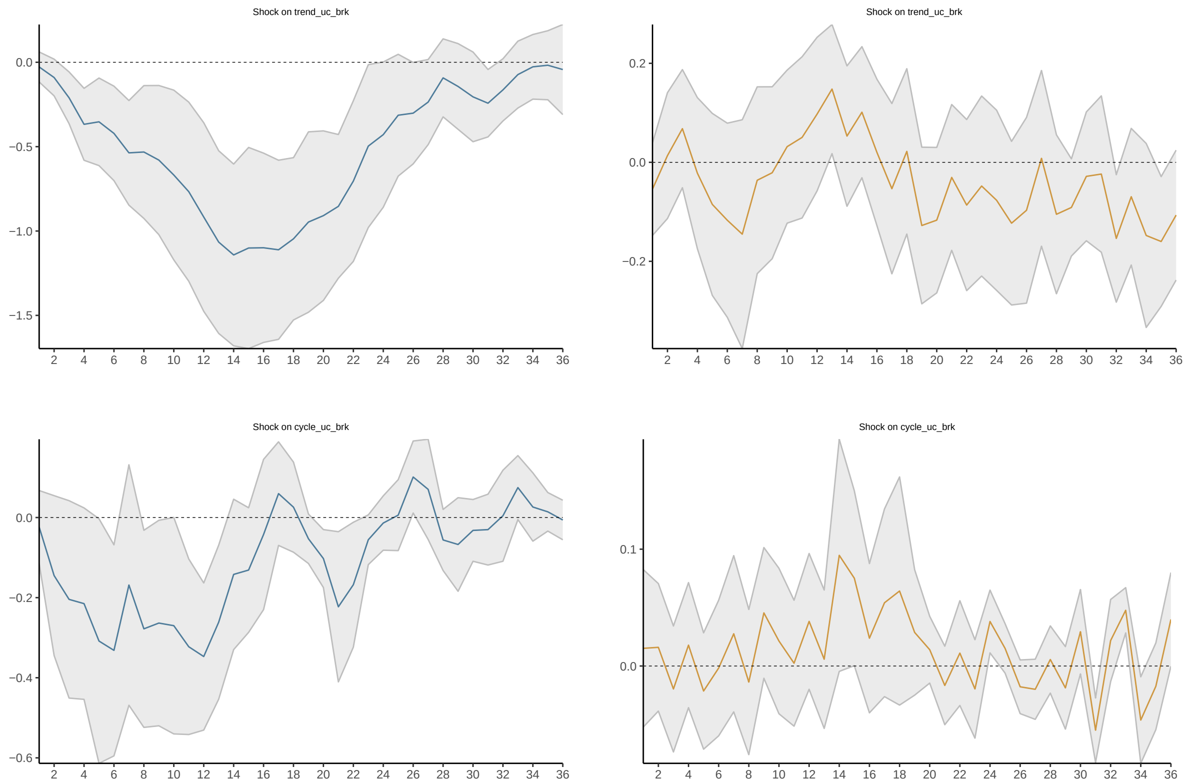
Note: The above figure shows the state-dependent impulse responses of inflation expectations to a one std. deviation shock to inflation sentiments. Inflation expectations were derived from our baseline UC model described in section 4. The *top panel* shows the impulse responses of long-run (trend) expectations whereas the *bottom panel* shows the response of short-run (cycle) expectations following the shock. The impulse responses are estimated using the nonlinear local projections approach described in equation (13). Impulse responses corresponding to the pre-FIT (2010M01:2016M09) are shown using solid blue line while solid yellow line shows the responses during the post-FIT (2016M10:2022M10) period. Shaded grey area shows the 90 per cent confidence interval around the mean estimate. Horizon, measured in number of months, is plotted along the horizontal axis.
Source: Authors' estimates.

Figure 8: State-dependent Impulse Responses of Long-run Inflation Expectations to Inflation Sentiment Shock: Robustness with Global Controls



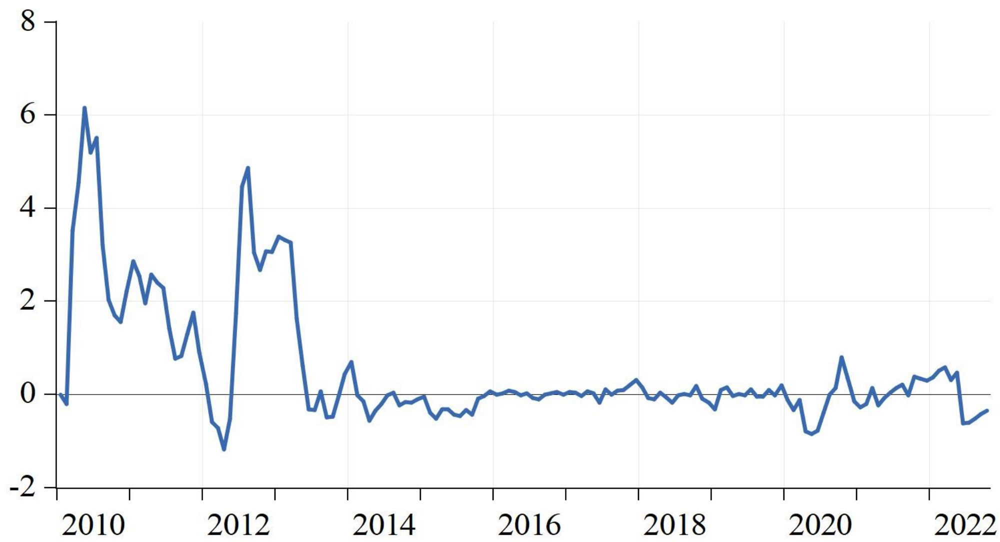
Note: The above figure shows the state-dependent impulse responses of inflation expectations to a one std. deviation shock to inflation sentiments. Inflation expectations were derived from our baseline UC model described in section 4. The *top panel* shows the impulse responses of long-run (trend) expectations whereas the *bottom panel* shows the response of short-run (cycle) expectations following the shock. The impulse responses are estimated using the nonlinear local projections approach described in equation (13) along with global control variables. Impulse responses corresponding to the pre-FIT (2010M01:2016M09) are shown using solid blue line while solid yellow line shows the responses during the post-FIT (2016M10:2022M10) period. Shaded grey area shows the 90 per cent confidence interval around the mean estimate. Horizon, measured in number of months, is plotted along the horizontal axis.
Source: Authors' estimates.

Figure 9: State-dependent Impulse Responses of Long-run Inflation Expectations to Inflation Sentiment Shock: Robustness using Model with Break in Variance



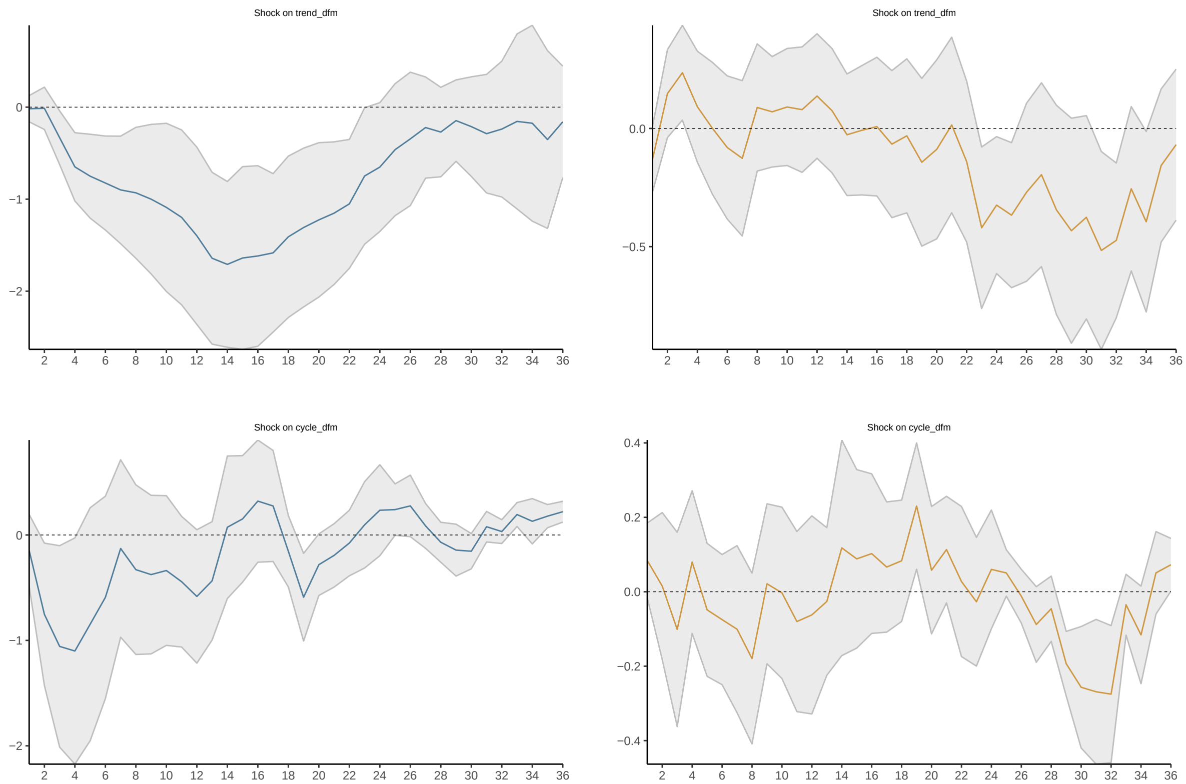
Note: The above figure shows the state-dependent impulse responses of inflation expectations to a one std. deviation shock to inflation sentiments. Inflation expectations were derived from UC model with break in variance described in section 4.2. The *top panel* shows the impulse responses of long-run (trend) expectations whereas the *bottom panel* shows the response of short-run (cycle) expectations following the shock. The impulse responses are estimated using the nonlinear local projections approach described in equation (13) along with global control variables. Impulse responses corresponding to the pre-FIT (2010M01:2016M09) are shown using solid blue line while solid yellow line shows the responses during the post-FIT (2016M10:2022M10) period. Shaded grey area shows the 90 per cent confidence interval around the mean estimate. Horizon, measured in number of months, is plotted along the horizontal axis.
Source: Authors' estimates.

Figure 10: Long-run (trend) and Short-run (cycle) Inflation Expectations from the DFM-SV Model



Note: The above figure plots the long-run (trend) and short-run (cycle) inflation expectations derived from the Dynamic Factor with Stochastic Volatility (DFM-SV) model described in section 6.3. The top panel plots the trend component while the bottom panel plots the cyclical component of one-year ahead inflation expectations for India.
Source: Authors' estimates.

Figure 11: State-dependent Impulse Responses of Inflation Expectations to Inflation Sentiment Shock: Robustness using the DFM-SV Model



Note: The above figure shows the state-dependent impulse responses of inflation expectations to a one std. deviation shock to inflation sentiments. Inflation expectations were derived from the DFM-SV model described in section 6.2. The *top panel* shows the impulse responses of long-run (trend) expectations whereas the *bottom panel* shows the response of short-run (cycle) expectations following the shock. The impulse responses are estimated using the nonlinear local projections approach described in equation (13) along with global control variables. Impulse responses corresponding to the pre-FIT (2010M01:2016M09) are shown using solid blue line while solid yellow line shows the responses during the post-FIT (2016M10:2022M10) period. Shaded grey area shows the 90 per cent confidence interval around the mean estimate. Horizon, measured in number of months, is plotted along the horizontal axis.
Source: Authors' estimates.

Figure 12: Deviation of Long-run Inflation Expectations from RBI's Inflation Target

Note: The above figure plots the difference between long-run (trend) inflation expectations derived from the our baseline UC model and the RBI's inflation target rate of 4.0 per cent from 2016 onwards.
Source: Authors' estimates.

Tables

Table 1: Inflation Correlation Matrix

Country	Australia	Brazil	Chile	Colombia	India	Indonesia	Malaysia	New Zealand	South Africa	South Korea	Turkey
Australia	1.00										
Brazil	0.25	1.00									
Chile	0.69	0.25	1.00								
Colombia	0.54	0.52	0.65	1.00							
India	0.20	-0.14	0.02	-0.27	1.00						
Indonesia	0.32	0.09	0.15	0.24	-0.00	1.00					
Malaysia	0.60	0.10	0.54	0.36	0.08	0.47	1.00				
New Zealand	0.84	0.15	0.64	0.46	0.10	0.19	0.44	1.00			
South Africa	0.38	0.20	0.49	0.40	0.27	0.27	0.42	0.23	1.00		
South Korea	0.77	0.33	0.50	0.55	0.22	0.28	0.49	0.75	0.37	1.00	
Turkey	0.63	0.35	0.55	0.60	-0.13	0.07	0.08	0.59	0.24	0.41	1.00

Note: The above table shows the contemporaneous correlation between headline consumer price inflation for a cross-country sample over the 2000-2020 period.
Source: Authors' estimates.

Table 2: Granger Causality Test: CPI Headline Inflation and Inflation Sentiment Index

		Lags	
hypothesis	h=1	h=2	h=3
Inflation *does not Granger cause* Sentiments	0.702 (0.40)	0.199 (0.82)	0.114 (0.95)
Sentiments *does not Granger cause* Inflation	6.453 (0.01)	2.718 (0.07)	2.389 (0.07)

Note: The above table shows the results for the Granger Causality test for CPI-based headline inflation and the news-based inflation sentiment index. For each hypothesis, the table reports the test F-statistic along with the p-value in the parentheses, across horizons.
Source: Authors' estimates.

Table 3: Sensitivity of 10-year Government Bond Yields to Inflation Sentiment Index

Variable	10Y Bond Yield (daily chg.)	
	Coefficient	p-value
Panel 1: 01/01/2010 - 30/09/2016		
Intercept	-0.0007	0.55
Inflation Sentiment (-1)	-0.0035	0.03
Panel 2: 01/10/2016 - 31/12/2021		
Intercept	-0.0004	0.74
Inflation Sentiment (-1)	0.0009	0.46

Note: The above table shows the coefficient estimates from regressing daily change in benchmark 10-year Indian Government Securities (GSec) yields on our news-based inflation sentiments index.
Source: Authors' estimates.

Table 4: Sensitivity of RBI-SPF Inflation Expectations to Actual Inflation

Variable	SPF_4Q		SPF_1Q	
	Coefficient	p-value	Coefficient	p-value
Panel 1: 2010Q3 - 2016Q2				
Intercept	3.35	0.00	2.13	0.00
Inflation(-1)	0.46	0.00	0.68	0.00
Panel 2: 2016Q3 - 2021Q4				
Intercept	4.57	0.00	2.95	0.00
Inflation(-1)	-0.03	0.76	0.34	0.00

Note: The above table shows the coefficient estimates from regressing median inflation expectations derived from the RBI-SPF survey on actual headline inflation. SPF_4Q is 4-quarter ahead median inflation forecast and SPF_1Q is 1-quarter ahead median inflation forecast from SPF survey
Source: Authors' estimates.

Table 5: Estimated Hyperparameters of the Baseline Model

AR	Estimate	SD	Estimate	Loadings	Estimate	Intercepts	Estimate
β	0.93 (0.00)	σ_τ	0.17 (0.00)			μ^τ	-0.01 (0.32)
		σ_c	0.17 (0.00)				
ϕ_1	0.67 (0.00)	σ_1	0.46 (0.00)	δ_1	1	μ_1	0.00
ϕ_2	0.65 (0.00)	σ_2	0.39 (0.00)	δ_2	0.34 (0.09)	μ_2	0.01 (0.96)
ϕ_3	0.65 (0.00)	σ_3	0.27 (0.00)	δ_3	0.05 (0.77)	μ_3	-0.28 (0.32)
ϕ_4	0.83 (0.00)	σ_4	0.18 (0.00)	δ_4	0.05 (0.74)	μ_4	-0.36 (0.15)
ϕ_5	0.70 (0.00)	σ_5	0.17 (0.00)	δ_5	0.18 (0.13)	μ_5	0.03 (0.89)
ϕ_6	0.57 (0.00)	σ_6	0.43 (0.00)	δ_6	0.93 (0.00)	μ_6	-0.11 (0.52)
ϕ_7	0.71 (0.00)	σ_7	0.23 (0.00)	δ_7	0.39 (0.02)	μ_7	0.10 (0.63)
ϕ_8	0.80 (0.00)	σ_8	0.39 (0.00)	δ_8	0.34 (0.09)	μ_8	0.01 (0.96)
ϕ_9	0.65 (0.00)	σ_9	0.21 (0.00)	δ_9	0.35 (0.01)	μ_9	-0.46 (0.02)
ϕ_{10}	0.71 (0.00)	σ_{10}	0.24 (0.00)	δ_{10}	1.56 (0.00)	μ_{10}	0.16 (0.37)
ϕ_{11}	0.46 (0.00)	σ_{11}	0.21 (0.00)	δ_{11}	-0.20 (0.34)	μ_{11}	-0.50 (0.10)
ϕ_{12}	0.49 (0.00)	σ_{12}	0.20 (0.00)	δ_{12}	0.38 (0.00)	μ_{12}	-0.05 (0.79)
ϕ_{13}	0.50 (0.00)	σ_{13}	0.24 (0.00)	δ_{13}	0.31 (0.04)	μ_{13}	-0.20 (0.34)
ϕ_{14}	0.73 (0.00)	σ_{14}	0.24 (0.00)	δ_{14}	0.11 (0.60)	μ_{14}	-0.01 (0.97)

Note: The above table provides the hyperparameter estimates from our baseline UC model described in Section 4. P-values are in parentheses.
Source: Authors' estimates.

Table 6: Regression Results for Deviation of Long-Run Expectation from Target

Variable	Coefficient	P-Value
Panel 1: 2016M10 - 2022M10		
Intercept	0.027	0.578
Lagged Deviation	0.984	0.000
Panel 2: 2016M10 - 2020M07		
Intercept	0.040	0.272
Lagged Deviation	0.914	0.000
Panel 3: 2020M08 - 2022M10		
Intercept	0.310	0.062
Lagged Deviation	0.843	0.000

Note: The above table provides the coefficient estimates derived from regressing deviation of long-run inflation expectations on its own lagged values across different samples during the 2016-2022 period.
Source: Authors' estimates.

Appendix A.1: Results from Model with Variance Breaks

Table 7: Estimated Hyperparameters from the Model with Breaks

AR	**Estimate**	**SD**	**Estimate**	**Loadings**	**Estimate**	**Intercepts**	
β	0.94 (0.00)	$\sigma_{\tau,pre}$	0.18 (0.00)			μ^{τ}	-0.06 (0.01)
		$\sigma_{\tau,post}$	1.94 (0.00)				
		$\sigma_{c,pre}$	0.23 (0.02)				
		$\sigma_{c,post}$	0.02 (0.15)				
ϕ_1	0.68 (0.00)	σ_1	0.51 (0.00)	δ_1	1	μ_1	0.00
ϕ_2	0.88 (0.00)	σ_2	0.22 (0.00)	δ_2	-0.02 (0.92)	μ_2	0.23 (0.13)
ϕ_3	0.90 (0.00)	σ_3	0.29 (0.00)	δ_3	0.27 (0.09)	μ_3	0.51 (0.52)
ϕ_4	0.82 (0.00)	σ_4	0.19 (0.00)	δ_4	0.10 (0.50)	μ_4	0.22 (0.07)
ϕ_5	0.35 (0.00)	σ_5	0.21 (0.00)	δ_5	0.16 (0.21)	μ_5	0.29 (0.00)
ϕ_6	0.74 (0.00)	σ_6	0.42 (0.00)	δ_6	1.07 (0.01)	μ_6	0.19 (0.93)
ϕ_7	0.79 (0.00)	σ_7	0.33 (0.00)	δ_7	0.34 (0.07)	μ_7	0.21 (0.00)
ϕ_8	0.54 (0.00)	σ_8	0.51 (0.00)	δ_8	0.28 (0.23)	μ_8	0.42 (0.09)
ϕ_9	0.72 (0.00)	σ_9	0.24 (0.00)	δ_9	0.30 (0.04)	μ_9	0.33 (0.00)
ϕ_{10}	0.50 (0.00)	σ_{10}	0.23 (0.00)	δ_{10}	1.88 (0.03)	μ_{10}	0.51 (0.30)
ϕ_{11}	0.35 (0.00)	σ_{11}	0.23 (0.00)	δ_{11}	-0.28 (0.41)	μ_{11}	0.24 (0.00)
ϕ_{12}	0.49 (0.00)	σ_{12}	0.23 (0.00)	δ_{12}	0.41 (0.00)	μ_{12}	0.23 (0.10)
ϕ_{13}	0.86 (0.00)	σ_{13}	0.21 (0.00)	δ_{13}	0.09 (0.70)	μ_{13}	0.23 (0.09)
ϕ_{14}	0.89 (0.00)	σ_{14}	0.28 (0.22)	δ_{14}	0.41 (0.03)	μ_{14}	0.21 (0.25)

Note: The above table provides the hyperparameter estimates from the UC model with break in variance described in Section 4.2. P-values are in parentheses.
Source: Authors' estimates.

Appendix A.2: Factor Loadings from the Dynamic Factor Model

Here, we present the median factor loadings from the dynamic factor model for each forecaster in our sample as shown in Table A.1.

Table A.1: Factor Loadings for Forecasters

Forecaster	**Factor 1**	**Factor 2**
1	0.70	0.01
2	0.57	0.07
3	0.70	-0.01
4	0.68	0.00
5	0.64	0.05
6	0.77	0.01
7	0.62	0.24
8	0.81	0.18
9	0.64	0.19
10	0.81	0.41
11	0.62	-0.09
12	0.66	0.11
13	0.72	0.02
14	0.85	-0.02

Note: The above table provides the median values of estimated factor loadings (weights) from the DFM-SV model described in Section 6.2. The model was estimated using Bayesian sampling techniques.
Source: Authors' estimates.

Appendix B: Decomposing Inflation Expectations: Univariate Models

Univariate UCSV Model for Median Inflation Forecast

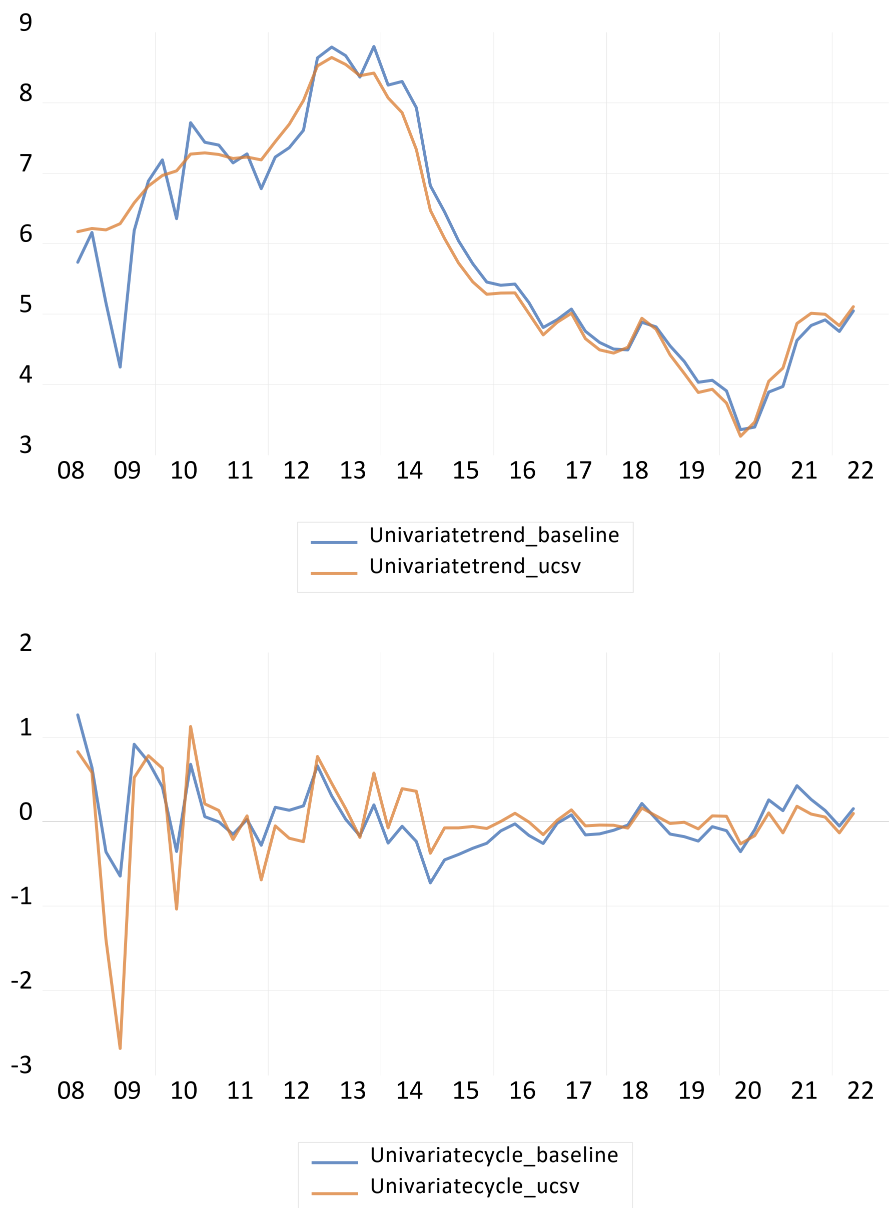
In this subsection, we compare the estimated trend and cycles from our univariate baseline model in section 6.3 with the Unobserved Components Stochastic Volatility (UCSV) model, as proposed by Stock and Watson (2007).

For the median inflation forecast, denoted as $\pi_{t,t+1}^{\text{median}}$, the inflation expectation can be decomposed into a trend component τ_t and an additional idiosyncratic noise component η_t.

The variances of these components in the Stock and Watson (2007) paper are modeled as evolving according to their own stochastic processes, typically assumed to follow a log-normal distribution, which allows for time variation in the volatility of the trend and cycle components.

The results for the UCSV model along with the baseline model are plotted below.

Figure 1: Comparison of Univariate Inflation Expectations Decomposition



Note: The above figure compares the long-run (trend) and short-run (cycle) inflation expectations derived from our univariate SPF forecast model with corresponding estimates from the UCSV model described in 6.3. The *top panel* shows the long-run (trend) expectations whereas the *bottom panel* shows the short-run (cycle) expectations from the baseline model (shown in solid blue line) and the UCSV model (solid yellow line).
Source: Authors' estimates.

Appendix C: Note on MissForest Algorithm – A Random Forest-based Missing Value Imputation Method

The MissForest algorithm, proposed by Stekhoven and Bühlmann (2012), is a non-parametric method for imputing missing values in a mixed-type data setting involving both continuous and categorical variables. The algorithm trains, i.e., estimates, a Random Forest (RF), a popular machine learning model introduced by Breiman (2001), on observed data to predict the missing part of the dataset. Following the discussion in Stekhoven and Bühlmann (2012), we briefly explain the algorithm below.

Let $X = (X_1, X_2, \ldots, X_p)$ be an $n \times p$ dimensional matrix requiring missing value imputation. Assuming an arbitrary variable X_s contains missing values at entries $i_{\text{mis}}^{(s)} \subseteq \{1, 2, \ldots, n\}$, the data can be divided into four categories:

(i) The non-missing values of variable X_s denoted by $y_{\text{obs}}^{(s)}$;

(ii) The missing values for X_s denoted by $y_{\text{mis}}^{(s)}$;

(iii) Variables other than X_s with observations $i_{\text{obs}}^{(s)} = \{1, 2, \ldots, n\} \setminus i_{\text{mis}}^{(s)}$, given by $x_{\text{obs}}^{(s)}$;

(iv) Variables other than X_s with observations $i_{\text{mis}}^{(s)}$, given by $x_{\text{mis}}^{(s)}$.

The algorithm begins by making an initial guess for all missing values in X using mean or median value imputation. Then the variables in X_s $(s = 1, \ldots, p)$ are sorted by the share of missing values in ascending order. Thereafter, for each variable X_s, the missing values are imputed by fitting an RF model with target variable $y_{\text{obs}}^{(s)}$ and predictors $x_{\text{obs}}^{(s)}$; following which the missing values $y_{\text{mis}}^{(s)}$ are predicted using the trained RF model and $x_{\text{mis}}^{(s)}$. The procedure is iterated until a stopping criterion γ is achieved. The stopping criterion is met as soon as the difference between the imputed data matrix over two consecutive iterations, namely ΔN, increases for the first time. For a set of numerical variables N, the difference is defined as

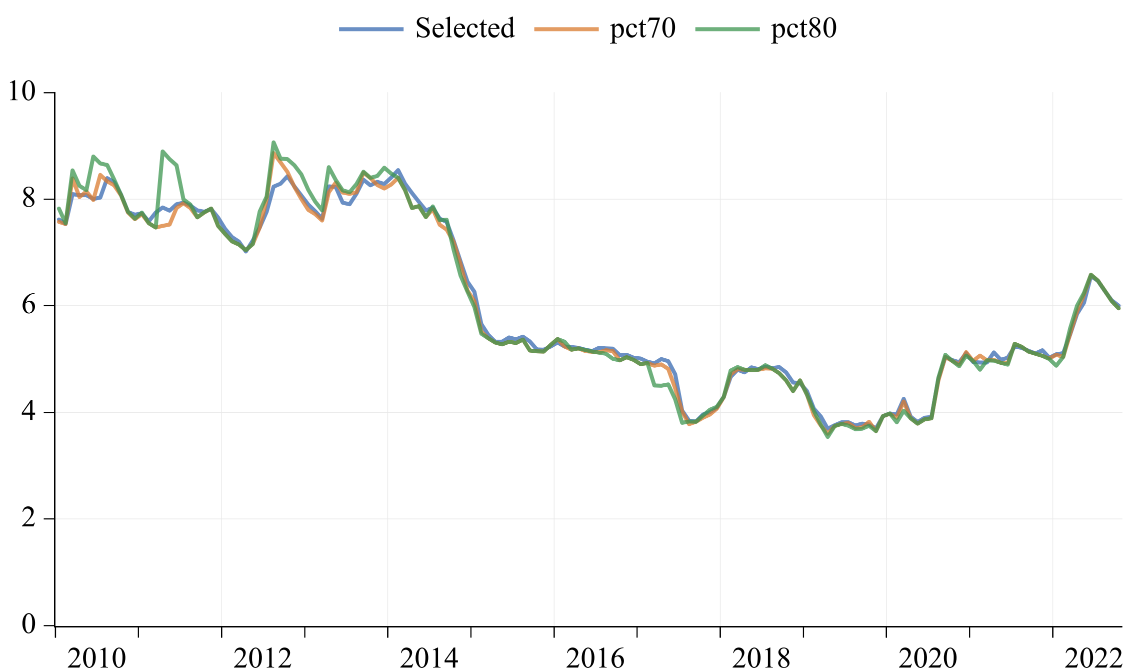
$$\Delta N = \frac{\sum_{j \in N} (X_{\text{new}}^{\text{imp}} - X_{\text{old}}^{\text{imp}})^2}{\sum_{j \in N} (X_{\text{new}}^{\text{imp}})^2}$$

Due to the underlying RF model, the algorithm described above has been shown to be robust to noisy data besides being highly capable in a high-dimensional data environment. Moreover, the non-parametric nature of the RF model allows the algorithm to leverage non-linear and interaction effects between predictors to improve forecast accuracy. As shown in

Stekhoven and Bühlmann (2012), the MissForest algorithm outperforms all other imputation algorithms. Therefore, we implement this algorithm to fill up the blanks in our forecaster-wise panel data of inflation forecasts for India. In our case, missing values (forecasts) could occur due to various reasons, such as if a given forecaster chose not to submit their forecast in a given period, or if their organization was merged with or acquired by other organizations. We keep track of the forecast series for each forecaster for such changes and clean the data accordingly. Applied to our case, the algorithm allows us to use information across both the cross-sectional and time dimensions for imputing missing values in the dataset. We also compare our results with a Kalman filter-based imputation algorithm for time-series data but find the imputed values to be inaccurate in most cases.

As mentioned earlier, the cutoff for a forecaster to remain in our sample was (i) provide inflation forecasts both before and after 2014; and (ii) report at least 60 percent of the full sample forecasts across time, including forecasts for both current and next year. It should be noted that if a forecaster missed even a single month of forecasts over the more than 12 years covered in our sample, that forecaster was classified as having a missing observation. This is a very stringent criterion, and unsurprisingly, only one forecaster in the sample reported forecasts without missing a single month. We also performed a robustness check with cutoffs of 70 percent and 80 percent, and the overall distribution of the forecasts remained consistent. Figure 2 below compares the median forecast across these different cutoffs, showing that the median forecasts align closely regardless of the threshold used.

Figure 2: Comparison of Forecasters Panel: Effect of Selection Criteria



Note: The above figure compares the median one year-ahead inflation expectations of our selected panel of forecasters (solid *blue* line) based on a 60 percent cutoff selection criteria with median forecasts from panels constructed using a 70 percent cutoff (solid *orange* line) and an 80 percent threshold (solid *green* line) criteria.
Source: Authors' estimates.