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

N. Kundan Kishor *   Bhanu Pratap †‡

Abstract

This paper explores the effects of India's adoption of inflation targeting (IT) as a monetary policy framework in 2016 on long-term inflation expectations in the private sector. Using data from 2010 to 2022, including inflation forecasts from professional forecasters and an inflation sentiment index derived from newspaper articles, our analysis assesses the impact of inflation sentiment on both long-run and short-run inflation expectations. Our findings suggest that post-2016, long-term inflation expectations became less sensitive to inflation sentiment, indicating that India's transition to IT may have contributed to anchoring these expectations in line with the central bank's target.

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 was initially pioneered by the Reserve Bank of New Zealand in 1990, and it has been embraced by central banks in 32 countries as their primary strategy for achieving and maintaining price stability. In 2016, the Reserve Bank of India (RBI) officially joined the ranks of inflation targeting (IT) practitioners, marking a significant policy transformation in one of the world's most populous and dynamically evolving economies.

As the IT regime continues to evolve and mature in India, it becomes paramount to assess its effectiveness in achieving its primary objectives. Measuring the success of such a policy transition encompasses multifaceted dimensions, but one particularly crucial aspect is the anchoring of long-term inflation expectations. Inflation expectations influence the behavior of economic agents, including consumers, businesses, and investors. When these expectations are well-anchored, they tend to align closely with the central bank's inflation target, fostering a stable economic environment.

Extensive research conducted over the past three decades, primarily in developed economies, has explored the relationship between IT and the anchoring of inflation expectations. The theoretical underpinnings of this relationship suggest that a successful IT regime should lead professional forecasters to adjust their predictions in a manner consistent with the central bank's inflation target. Consequently, this alignment contributes to the anchoring of inflation expectations. The concept of anchoring, as emphasized by Bernanke (2007), posits that inflation expectations are anchored when long-term expectations remain relatively unaffected by incoming data and short-term fluctuations.

India's transition to an IT framework represents a critical policy shift, given its unique economic and institutional context (Chakravarty, 2020; Dua, 2023). Understanding how this transition has influenced the expectations of private sector forecasters is crucial for several reasons. Firstly, it sheds light on the adaptability and effectiveness of the IT framework in an emerging market economy like India. Secondly, it enables policymakers to gauge the extent to which the IT regime has succeeded in achieving its primary objective: maintaining price stability. Thirdly, by observing the behavior of private sector forecasters, one can gain insights into whether the introduction of IT has indeed led to the anchoring of inflation expectations in the Indian context.

To investigate the impact of the introduction of the IT regime in India on inflation expectations, this research employs a dataset of professional forecasters comprising one-year ahead inflation expectations spanning from January 2010 to October 2022. In addition, we also use text-mining techniques to create an inflation sentiment index based on newspaper articles in India. The empirical strategy used to examine the responsiveness of long-run inflation expectations to incoming data is based on two steps. In the first step, we decompose one-year ahead inflation expectations into a trend and a cycle. The trend in this setup captures the long-horizon inflation expectations, and the cycle captures short-run movements in inflation forecasts. This approach is motivated by Stock and Watson (2007). It distinguishes between long-term inflation expectations, modeled as a trend in forecasts, and short-term expectations, represented by the cyclical component. The trend is modeled as a random walk representing the slow evolution of long-run inflation expectations. Since we have a panel of individual forecasters, the common trend among the forecasters captures the long-run cointegrating relationships. The common cycle across forecasters captures the short-run movements in inflation expectations.

In the second step, we use local projections to estimate the response of long-run and short-run inflation expectations to incoming data as measured by the inflation sentiment index. To do so, we employ the state-dependent impulse response analysis method introduced by Jorda (2005), allowing for different responses across the pre- and post-IT regime. Given the significant public policy implications of the IT's impact on the anchoring of inflation expectations, many researchers have examined this topic through various lenses. Chinoy, Kumar, and Mishra (2016), one such early study in the Indian context, examined the impact of adopting the inflation targeting (IT) framework in India using a Phillips curve framework. They found that the adoption of the IT regime was responsible for about one-third of total disinflation experienced in India after 2014. Asnani, Kumar, and Tomar (2019), on the other hand, used survey data on household inflation expectations to show that the adoption of the IT regime in India led to anchored inflation expectations as evidenced by a muted spillover from food inflation to both food and non-food inflation expectations. More recently, using aggregate inflation expectations of households to estimate an inflation expectations anchoring index, Pattanaik, Nadhanael, and Muduli (2023) also provide further evidence on improved anchoring performance following the adoption of the IT regime as a monetary policy framework in India.

Similarly, in a related paper, Garga, Lakdawala, and Sengupta (2022) examined the impact of IT adoption on the expectations of financial markets, analyzing the change in the market's perception following IT implementation. They found that the market interpreted the adoption of IT as a credible commitment by the RBI, perceiving a stronger response to inflation in the monetary policy reaction function following the transition. Our paper adopts a different approach; instead of focusing on the perception of the monetary policy reaction function, we explore the impact of IT adoption on long-horizon inflation expectations of professional forecasters. In doing so, we are motivated by Bernanke (2007) and Svensson (2007), who contend that a credible monetary policy in the form of the IT regime leads to the anchoring of inflation expectations, rendering long-run inflation expectations insensitive to incoming news about inflation.

We find that the private sector forecasters' long-run inflation expectations, as measured by inflation trend, began to moderate before the formal introduction of the IT regime. These long-run inflation expectations stabilized around 5.5-6 percent for the next four years. In terms of the effectiveness of the IT regime, we find that long-horizon inflation expectations in India have exhibited decreased responsiveness to inflation sentiment following the official adoption of the IT regime in 2016. In contrast, the pre-2016 period witnessed significant sensitivity of long-run inflation expectations to changes in inflation sentiment. Moreover, the response to inflation sentiment appears to be U-shaped, with positive sentiment shocks (good news about inflation) leading to an immediate decline in long-horizon inflation expectations, peaking around 16 months, and displaying substantial persistence.

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 these 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 remainder of the paper is organized as follows: Section 2 provides a background on India's adoption of the inflation targeting regime. Section 3 provides a summary of related literature, Section 4 describes the forecast data as well as construction of the inflation sentiment index; Section 5 presents the trend-cycle decomposition model used in our paper; Section 6 presents the results from local projection model; and Section 7 concludes.

2 Background

The history of monetary policy strategy in India has witnessed significant evolution over the years.[1] The Reserve Bank of India (RBI), established in 1935, is responsible for the

[1] 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.

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 commission 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 1983. 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 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 of 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, Gupta, and Choudhary (2021) and RBI (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, Surti, and Tomar, 2020; Samanta and Kumari, 2021).

3 Brief Literature Review

The literature on the impact of inflation targeting on macroeconomic outcomes is extensive. In this paper, our objective is to examine the effect of the introduction of the IT regime in India on the anchoring of long-run inflation expectations. To achieve this, we focus on the literature that has explored the interrelationship between the IT regime, the credibility of monetary policy, and the anchoring of inflation expectations. The anchoring of long-run inflation expectations holds significant importance within the context of inflation targeting. When expectations are well-anchored, it instills confidence among economic agents, including households and businesses, that future inflation will closely align with the central bank's target. This confidence, in turn, influences their decisions regarding wage and price-setting, thereby impacting actual inflation outcomes.

Numerous empirical studies have investigated the impact of inflation targeting on the anchoring of long-run inflation expectations. In a seminal work on the effectiveness of IT, Svensson (2007) discusses the role of commitment and flexibility in inflation targeting, emphasizing the necessity of a credible commitment to anchor expectations effectively. Svensson's insights underscore the pivotal role of central bank commitment in maintaining the stability of long-run inflation expectations. Bernanke (2007) delves into the relationship between inflation expectations and monetary policy, emphasizing the central role of inflation expectations in shaping monetary policy and the importance of policymakers considering these expectations when making policy decisions. Bernanke's work highlights that anchoring inflation expectations is a key objective for central banks and contributes to economic stability. Specifically, he argues that in the case of a credible monetary policy regime, long-run inflation expectations should remain insensitive to incoming data. In this regard, Gurkaynak, Sack, and Swanson (2005) examine the sensitivity of long-term interest rates to economic news, indirectly influencing inflation expectations. Their findings underscore the broader impact of economic information on financial markets and its subsequent effect on inflation expectations. As the credibility of inflation targets wanes, expectations can exhibit rapid shifts in response to changing economic and policy conditions. Cross-country evidence presented by Gurkaynak, Levin, and Swanson (2005) highlights the variability in the effectiveness of inflation targeting in anchoring expectations, with some countries successfully anchoring long-run inflation expectations while others exhibit sensitivity to economic news, indicating that the impact of inflation targeting on expectations can vary across nations.

Effective communication plays a crucial role, as emphasized by Mishkin and Schmidt-Hebbel (2007), in shaping long-term inflation expectations. Clear communication and a commitment to price stability are instrumental in anchoring expectations and achieving policy objectives. Expectations, as underscored by Evans and Honkapohja (2001), are central to shaping economic outcomes, necessitating adept management of inflation expectations by central banks to effectively pursue their policy objectives. Economic news can significantly influence public understanding of monetary policy and its impact on inflation expectations, as explored by Carvalho and Nechio (2014). Davis and Presno (2014) investigate whether the adoption of inflation targeting has facilitated the anchoring of inflation expectations across various countries. Their findings reveal discernible differences in the response of inflation expectations to shocks, underscoring the potential contribution of inflation targeting to anchoring expectations. Finally, Bems et al. (2021) explore the influence of inflation expectations' anchoring on inflation persistence, suggesting that well-anchored expectations can mitigate the persistence of inflation in response to external shocks.

One strand of the literature focuses on the impact of inflation targeting on expected inflation levels. Johnson's research (2002) reveals a consistent trend: the announcement of inflation targets leads to a decline in expected inflation levels. Importantly, this decline persists even after accounting for various factors, suggesting that inflation targeting can effectively anchor inflation expectations by reducing the level of expected inflation. Another aspect of the literature delves into the variability of expected inflation and forecast accuracy post-inflation targeting. Surprisingly, studies suggest that while inflation targeting stabilizes the level of expected inflation, it may not significantly reduce variability or improve forecast accuracy. This nuance underscores that inflation targeting primarily manages the level of expected inflation rather than its variability or forecast precision. The transition to a flexible average inflation-targeting (FAIT) regime, as examined by Naggert, Rich, and Tracy (2021), sheds light on the potential influence of adopting a new monetary policy framework. Their findings suggest that the adoption of FAIT can have a notable impact on anchoring inflation expectations, fostering a more stable outlook. Kara's research (2021) explores the role of policy performance in shaping inflation expectations, emphasizing that the effectiveness of inflation targets depends on policy performance.

While the literature generally supports the notion that inflation targeting can anchor long-run inflation expectations effectively, it is not without challenges. Some studies have highlighted the potential limitations of inflation targeting in addressing factors such as asset price bubbles and supply-side shocks. Coibion and Gorodnichenko (2012) challenge conventional assumptions about the intricate interplay between monetary policy, trend inflation, and inflation expectations, providing a deeper understanding of these complex dynamics and shedding light on the intricate relationships at play. Their study found that changes in inflation expectations were closely linked to changes in actual inflation.

Our paper is also related to the trend-cycle decomposition literature, which has been extensively applied to inflation since Stock and Watson (2007). The underlying idea is that inflation can be decomposed into a slow-moving component captured by the trend and a cyclical component. Our paper utilizes this approach and decomposes 1-year ahead inflation forecasts into a trend that captures long-horizon forecasts and a cycle representing temporary movements in inflation.

4 Data and Preliminary Evidence

4.1 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 consumer price inflation (CPI, YoY%) for our purpose.[2] 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. We retain only those forecasters in our sample which (i) participated in the survey and provided inflation forecasts prior to 2014; and (ii) did not have more than 40 percent missing observations across time. Out of all forecasters in the survey, a total of 14 professional 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 some missing observations for some participants.

To impute these missing observations, we utilize a non-parametric, machine learning-based algorithm. In particular, we implement an imputation algorithm based on a *Random Forest* model proposed by Stekhoven and Bühlmann (2012). The algorithm begins by imputing missing data using the mean or mode value for a given variable or data series. Then, for each variable/data series containing missing values, a random forest model is trained on the observed data and is used to predict the missing values. This process of training and prediction is applied in an iterative manner until a stopping criterion is satisfied or the maximum number of user-defined iterations is reached.[3] Applying this technique to our dataset provides us with a complete panel of inflation forecasts across different horizons.

The survey participants offer their projections for both the current and the upcoming calendar year. Consequently, the survey data generate 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:

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

As explained in Dovern et al. (2012), the November 2018 forecast of inflation rate be-

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

[3]The algorithm is implemented in R using the *missForest* package. Interested readers may refer to Stekhoven (2011) and Stekhoven and Bühlmann (2012) for details on the algorithm.

tween 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.

4.2 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.[4] 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. [5] 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). In essence, this approach involves matching words (or groups of words) in a document with a predefined list of polarized (positive and negative) terms, assigning numerical scores to each matched word based on its positive or negative tone. For our analysis, we utilize the Loughran-McDonald lexicon, which is specifically designed for analyzing economic and financial texts (Loughran and McDonald, 2011). Moreover, our approach 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 document. It may be noted that we perform our sentiment computation at the sentence-level for more efficient scoring.

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

[5]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.*

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 1). 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.

4.3 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 2. 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 3, 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 2 and 3, 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 two 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.

5 Decomposition of Inflation Forecasts into a Trend and a Cycle

As described in the data description section, our dataset consists of forecasts of inflation 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 justifiable to assume that these forecast series exhibit comparable long-term and medium-term characteristics. Specifically, we make the assumption that these series share a common trend and cycle, and we employ state-space methods to extract these components. This is motivated by Stock and Watson (2007), who distinguish between persistent and short-term movements in inflation. In our study, the inflation forecasts of these forecasters are characterized by their persistence and co-movement. To account for these features, we incorporate a common trend and cycle across all the forecasters. Additionally, we consider short-term noise in each individual forecaster's forecast, captured by an idiosyncratic white noise component. The use of a multivariate model enhances the precision of our estimates for PCE inflation's trend and cycle.[6]

Since there are 14 forecasters in our analysis providing 1-year ahead inflation expectations, we decompose each forecaster's forecast into a trend, a cycle and idiosyncratic component. For expositional purpose, we outline a model with three forecasters below. 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. An alternative model would be to have all the loadings equal. This may be too restrictive given that we are already assuming a common trend with equal loading for all forecasters. The idiosyncratic factors also follow an AR(1) process. The shocks to these factors are joint-normally distributed with mean zero.[7]

The corresponding transition equations included in the model are:

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

$$c_t = \beta c_{t-1} + u^c_t, u^c_t \sim iidN(0, \sigma^2_c) \tag{5}$$

$$\eta^i_t = \phi_i \eta^i_{t-1} + \epsilon^i_t, u^c_t \sim iidN(0, \sigma^2_i) \tag{6}$$

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

[6]The multivariate approach has been shown to be useful in a state-space setting by Clark (1989), Basistha and Nelson (2007), and Basistha and Startz (2008).

[7]See Morley *et al.* (2003) for a discussion of unobserved components models with correlated error terms.

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

The transition equation has the following representation:

$$
\begin{bmatrix} \tau_t \\ c_t \\ \eta^1_t \\ \eta^2_t \\ \eta^3_t \end{bmatrix} = \begin{bmatrix} \mu^\tau \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & \beta & 0 & 0 & 0 \\ 0 & 0 & \phi_1 & 0 & 0 \\ 0 & 0 & 0 & \phi_2 & 0 \\ 0 & 0 & 0 & 0 & \phi_3 \end{bmatrix} \begin{bmatrix} \tau_{t-1} \\ c_{t-1} \\ \eta^1_{t-1} \\ \eta^2_{t-1} \\ \eta^3_{t-1} \end{bmatrix} + \begin{bmatrix} u^\tau_t \\ u^c_t \\ \epsilon^1_t \\ \epsilon^2_t \\ \epsilon^3_t \end{bmatrix} \tag{8}
$$

The transition-equation error terms are joint-normally distributed with mean zero and with no restrictions on their contemporaneous covariances. 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.[8]

The estimated hyperparameters for this model are shown in Table 3. There are total 58 parameters in our model: 14 intercepts, 15 AR parameters, 16 standard errors and 13 loading parameters. There are a few interesting observations that can be made from these estimates: the relative importance of shocks to trend and cycles . The loadings on common cycles are positive implying positive comovement in the cycles even if we do not impose any restrictions on these loadings. The persistence parameter for the common cycle is 0.93, implying a half-life of around 7 months. For most of the forecasters, the standard errors of idiosyncratic factor are higher than volatility of trend and the common cycle. The intercepts capture the mean differences in inflation forecast of different forecasters. The estimates from the model also suggest that we do not suffer from the pile-up problem that is usually associated with insignificant standard errors in unobserved component models[9].

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

[8]For the details on the estimation procedure, see Chapter 2 of Kim and Nelson (2000).
[9]See Stock and Watson (1998).

inflation in the UC model is assumed to capture the long-run inflation expectation of the private sector forecasters. The estimated inflation trend and cycles from this UC model is 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 inflation 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.

We also observe similar pattern for inflation cycle as shown in 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. Since cycle is the difference between inflation forecast and inflation trend, we find that inflation cycle on average is lower in the later part of the sample. In the section below we examine how these long-run inflation expectations as measured by trend and short-run inflation expectations as measured by cycle respond to inflation sentiment in the newspapers.

5.1 Another Variant

One concern about the unobserved component model in the previous section is its lack of consideration for time-varying volatility in inflation. To address this concern, we can employ 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. These features are incorporated into our dynamic factor model, as described below. In addition to estimating the model, this approach also enables us to determine the optimal number of factors. In our case, the model selects two factors, implying r=2.

The multi-factor stochastic volatility model decomposes the variations in inflation expectations into two components. Specifically, the model is given by

$$\pi_{t,t+1} = \Lambda \cdot f_t + \Sigma_t^{\frac{1}{2}} \varepsilon_t, \varepsilon_t \sim N_m(0, I_m) \tag{9}$$

$$f_t = V_t^{\frac{1}{2}} u_t, u_t \sim N_r(0, I_r) \tag{10}$$

where $\mathrm{y}_t = (y_{1t}, y_{2t}, \ldots .y_{mt})'$ consists of m observed time series. Let f_t be a vector of r unobserved latent factors. $\Sigma_t = Diag(\exp(h_{1t}), \ldots . \exp(h_{mt}))$,$V_t = Diag(\exp(h_{m+1,t}), \ldots . \exp(h_{m+r,t}))$ and Λ is an unknown $m \times r$ matrix with elements Λ_{ij}. In the static factor model, it is assumed that observations are influenced by latent factors and idiosyncratic innovations with constant variances. However, in the case of the factor stochastic volatility model, both idiosyncratic innovations and latent factors are permitted to exhibit time-varying variances, contingent upon $m + r$ latent volatilities. In line with the broader literature on factor models, we also maintain the assumption that shocks to the common and idiosyncratic components are mutually orthogonal. Furthermore, the latent factors and idiosyncratic factors can each follow distinct stochastic volatility processes.:

$$h_{it} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \sigma_i \eta_{it}, \eta_{it} \sim N(0, 1) \tag{11}$$

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 (2017) introduces 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. For a comprehensive understanding of the estimation process, please refer to Kastner (2017) and Hossjezni and Kastner (2020). 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 inflation trend and cycle derived from this approach in Figure 6. 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's 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.

6 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 Jorda (2005). 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:

$$y_{t+h} = \alpha_h + \beta_h \cdot shock_t + \gamma \cdot \varkappa_t + \varepsilon_{t+h} | h = 1, 2, ...H \tag{12}$$

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. Interested readers may refer to Jordà (2023) for an excellent review of the local projections approach. The linear local projection model can be easily extended to account for state-dependence as follows:

$$y_{t+h} = \alpha_h + \delta_r \cdot \{\beta_h^{R1} \cdot shock_t\} + (1-\delta_r) \cdot \{\beta_h^{R2} \cdot shock_t\} + \gamma \cdot \varkappa_t + \varepsilon_{t+h} | h = 1, 2, ...H \quad (13)$$

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 12 lags of y along with one-period lagged values of Index of Industrial Production (IIP, YoY%), nominal US dollar-Indian Rupee exchange rate (USD-INR, 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 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) prior to 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 the UC 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. The results from the local projection analysis are shown in Figures 7 and 8.

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's (2007) 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 Figure 8, 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 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 perform the same analysis for inflation trend and cycles obtained from the dynamic factor model. As shown in Figures 9 and 10, the results are robust to this change in the model specification.

7 Conclusions

The adoption of inflation targeting by the RBI marked a significant policy shift in the Indian economy. To assess its impact, we investigated whether this shift anchored long-term inflation expectations, a vital element for the effectiveness of IT. Using a dataset of 14 professional forecasters from January 2010 to October 2022, we analyzed inflation expectations before and after the introduction of the IT regime in 2016. Prior to IT adoption, long-term inflation expectations, measured by the common trend in 1-year ahead inflation forecasts, were highly responsive to changes in inflation sentiment, indicating sensitivity to economic news and events. However, this responsiveness significantly diminished post-IT, with long-horizon inflation expectations becoming insensitive to inflation sentiment. There was no difference in the responsiveness of short-term inflation expectations to inflation sentiment between the pre- and post-IT regimes. These findings provide evidence that the IT regime has effectively reduced the impact of short-term fluctuations and economic news on inflation expectations, aligning with the idea that credible monetary policy, in the form of IT, can anchor inflation expectations.

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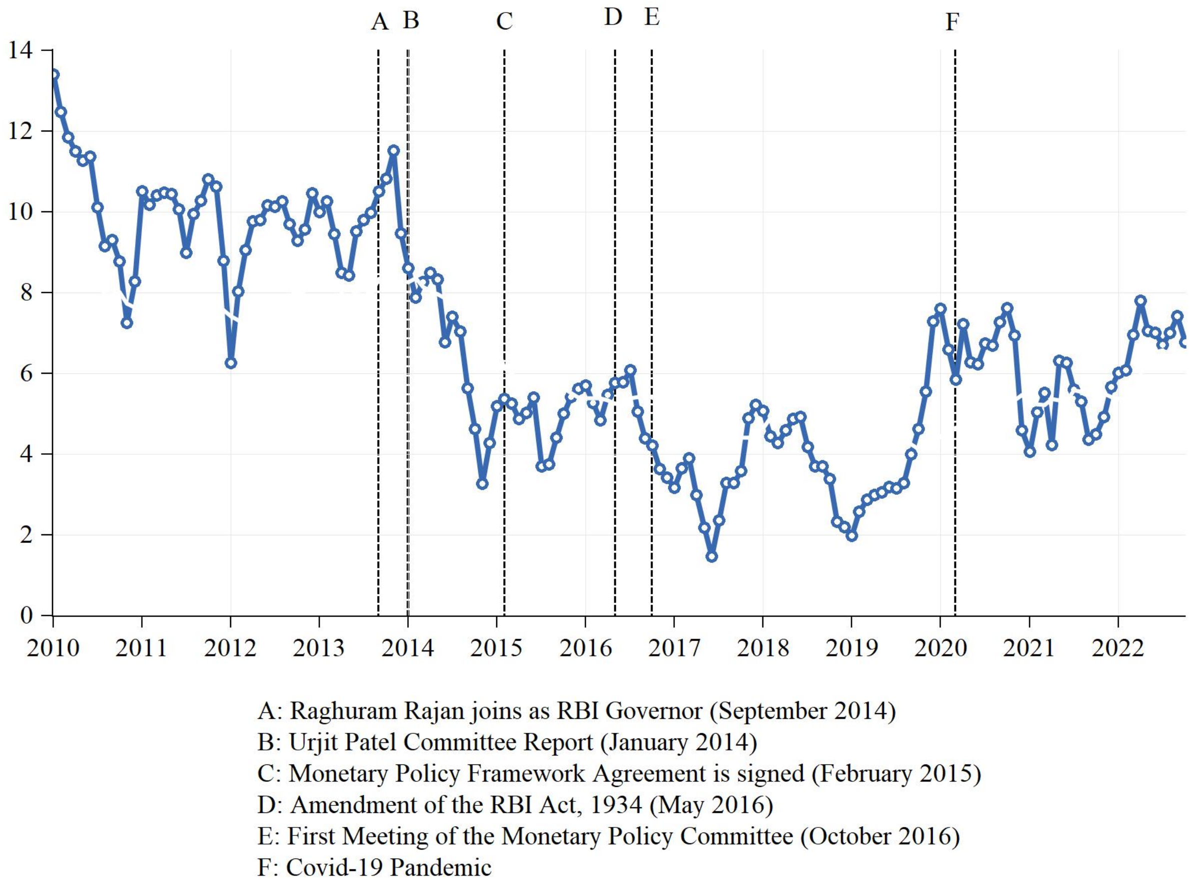

Figure 1: India's transition to Inflation Targeting and CPI Headline Inflation

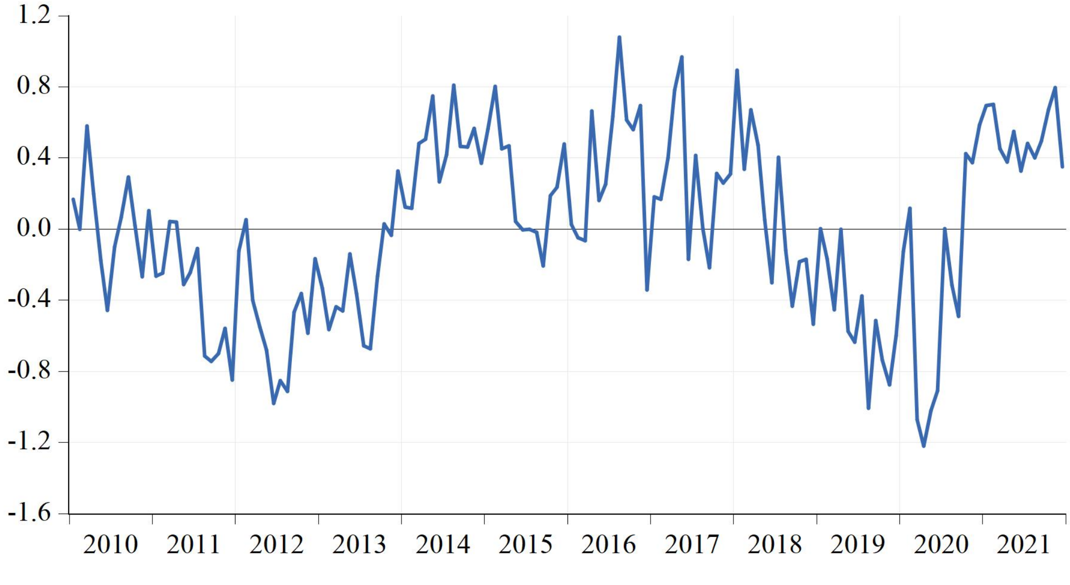

Figure 2: Newspaper-based Inflation Sentiment Index for India

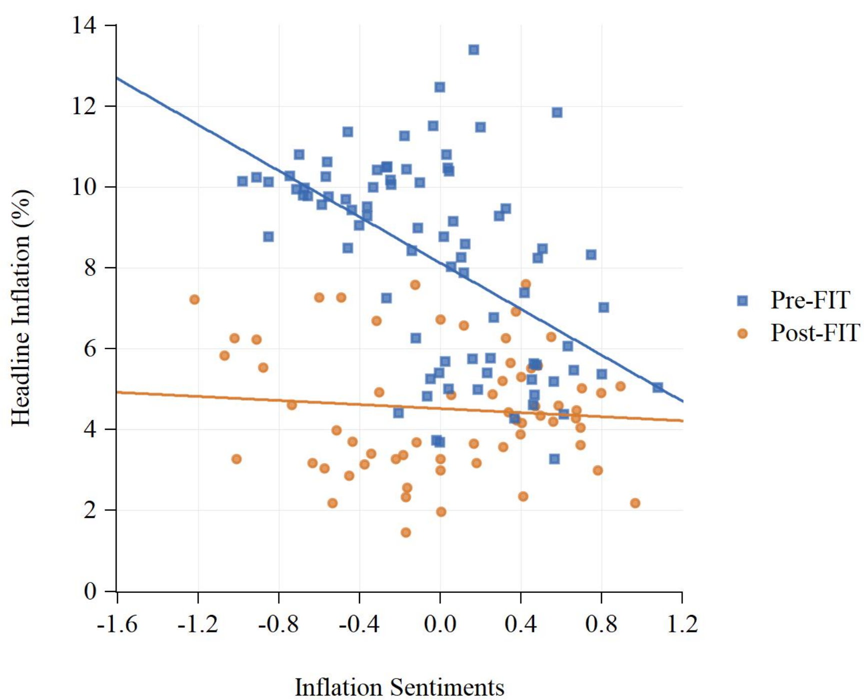

Figure 3: Headline Inflation and News-based Inflation Sentiment Index for India

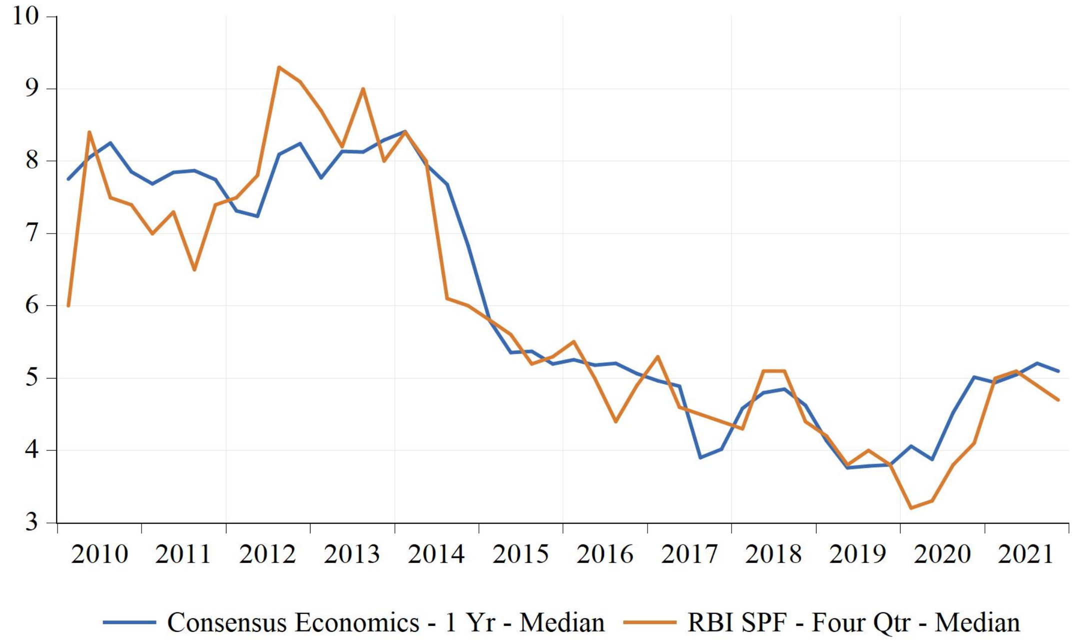

Figure 4: Comparison of 1-year ahead Inflation Forecasts

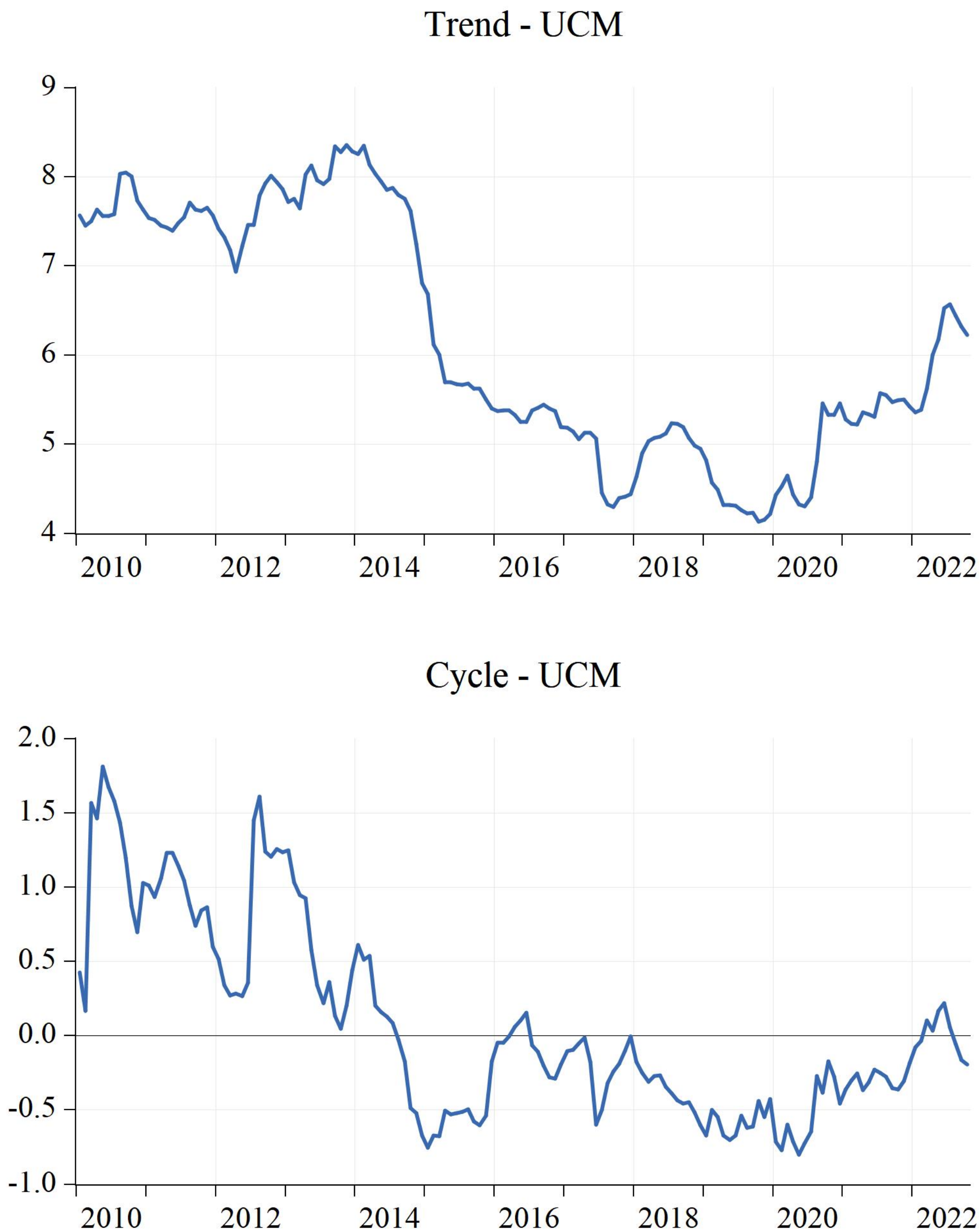

Figure 5: Long-run (Trend) and Short-run (Cycle) Inflation Expectation from Unobserved Component Model

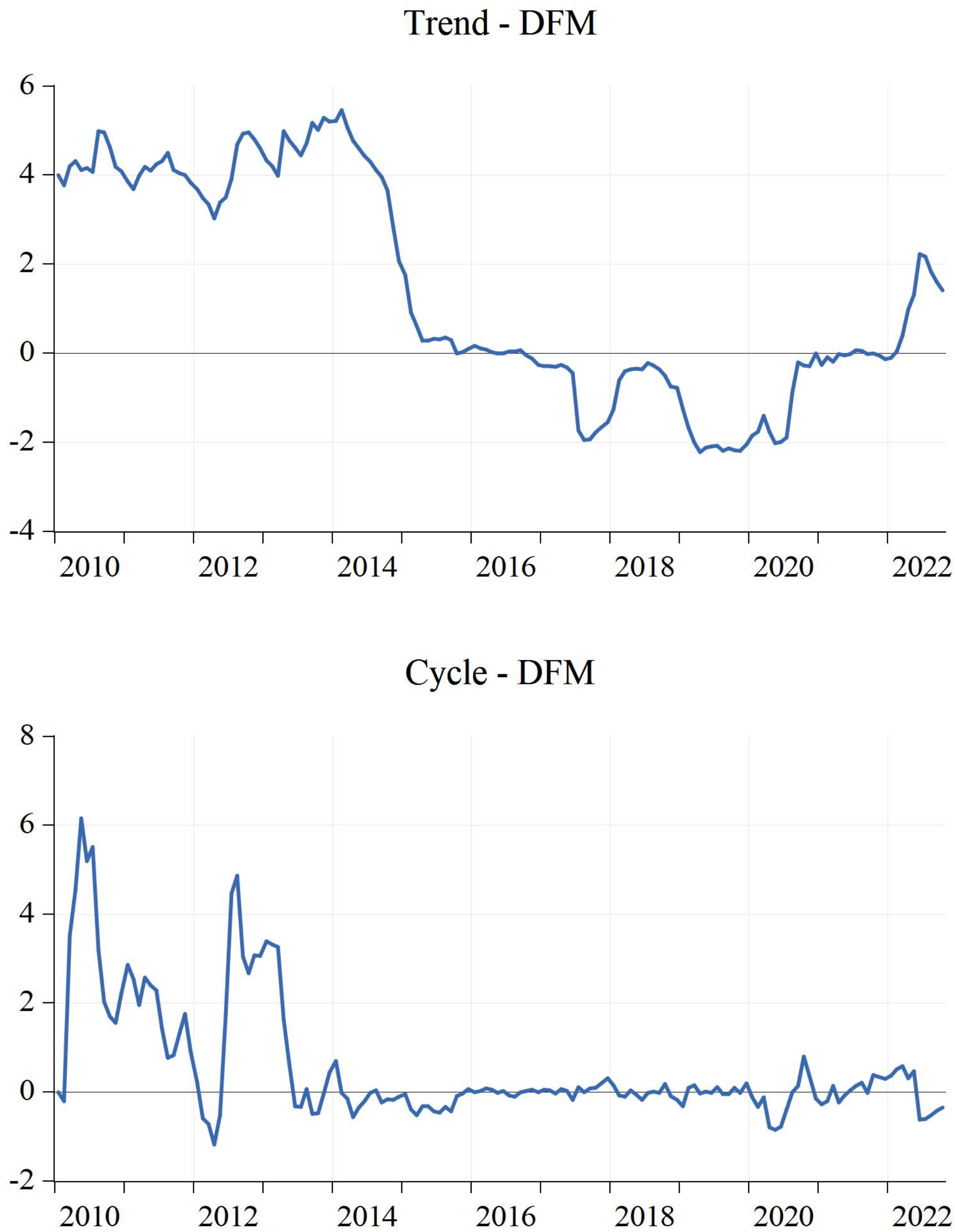

Figure 6: Long-run (Trend) and Short-run (Cycle) Inflation Expectation from Dynamic Factor Model

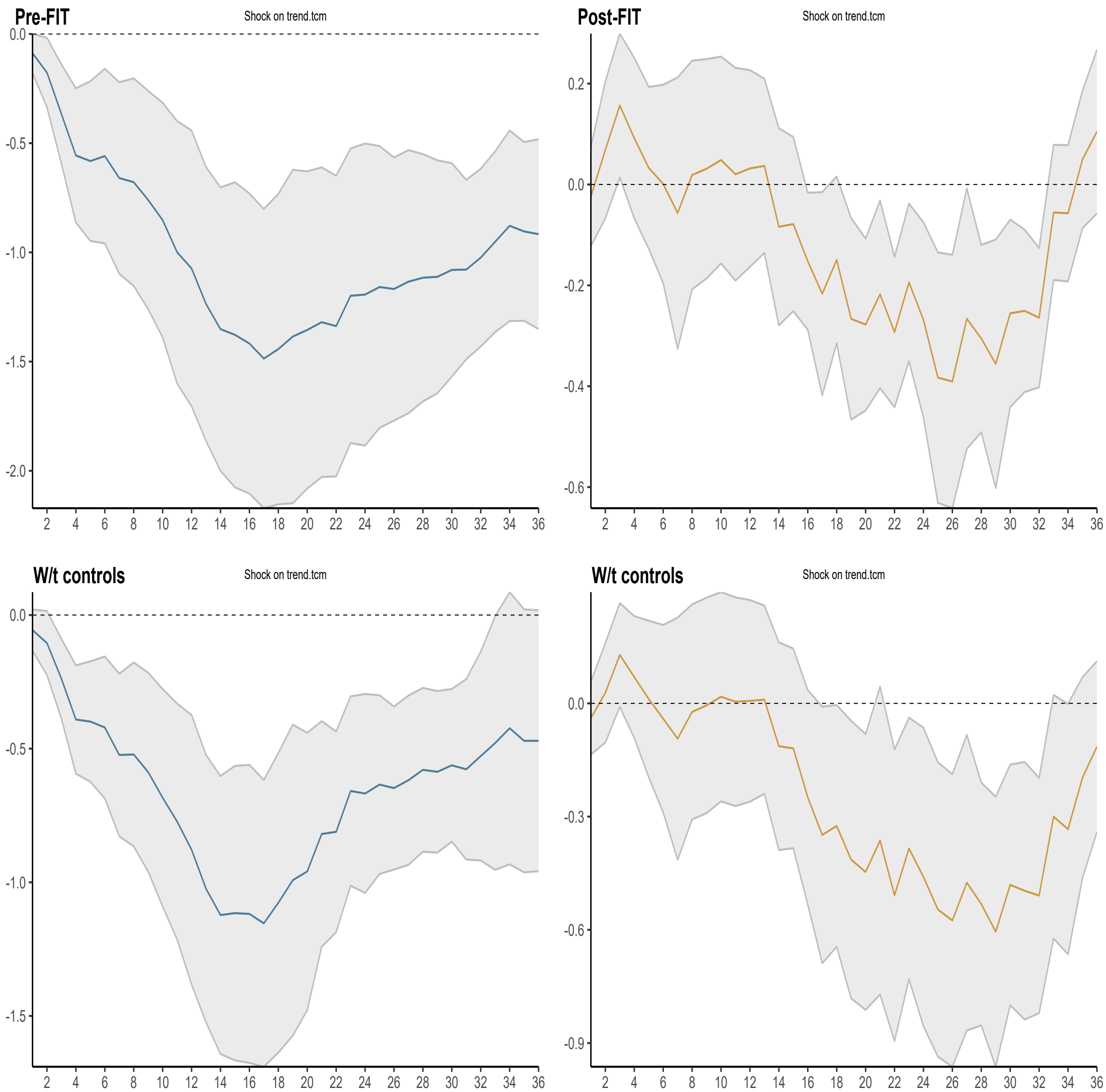

Figure 7: State-dependent Impulse Responses of Long-run Inflation Expectations to Inflation Sentiment Shock

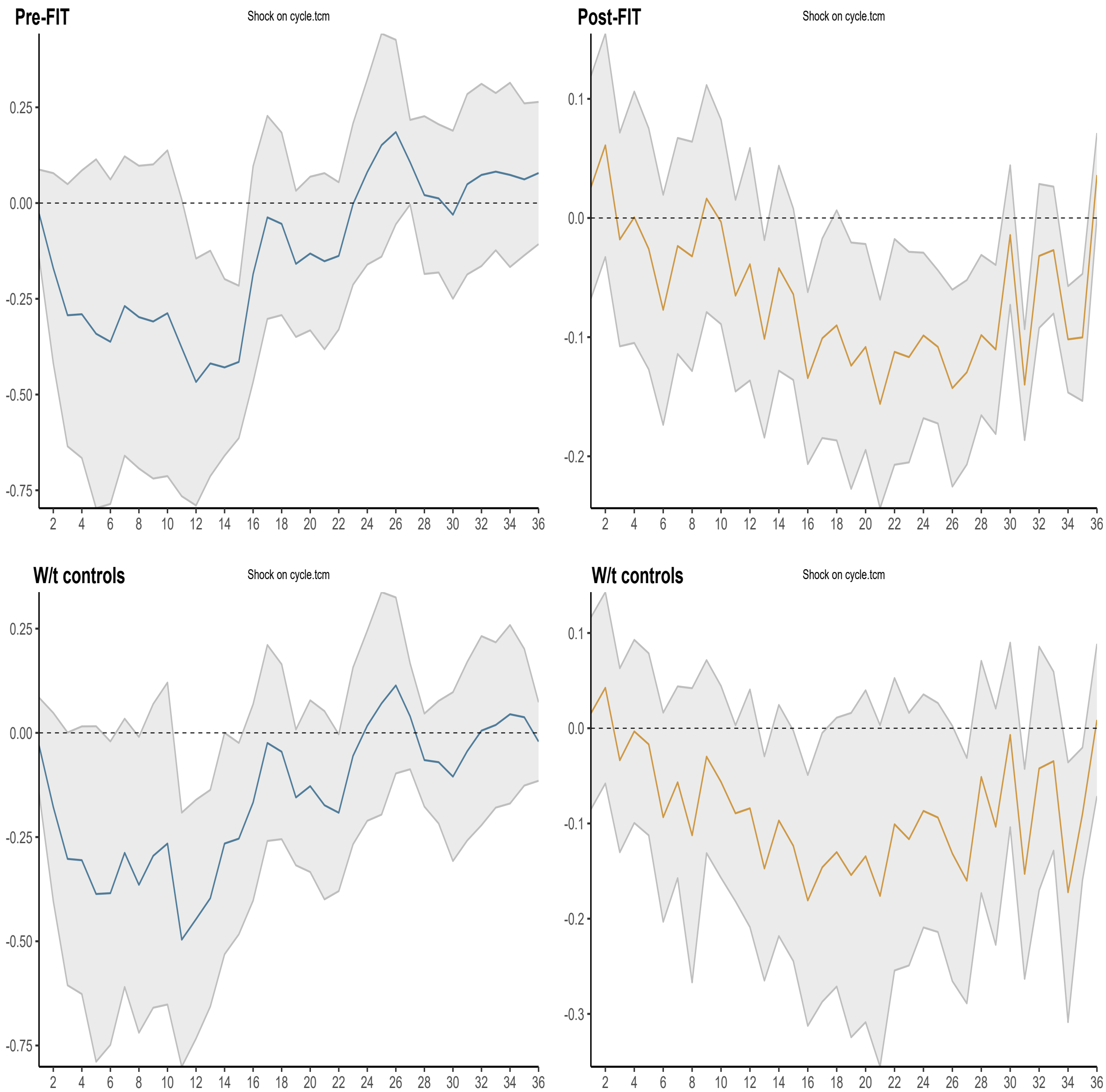

Figure 8: State-dependent Impulse Responses of Short-run Inflation Expectations to Inflation Sentiment Shock

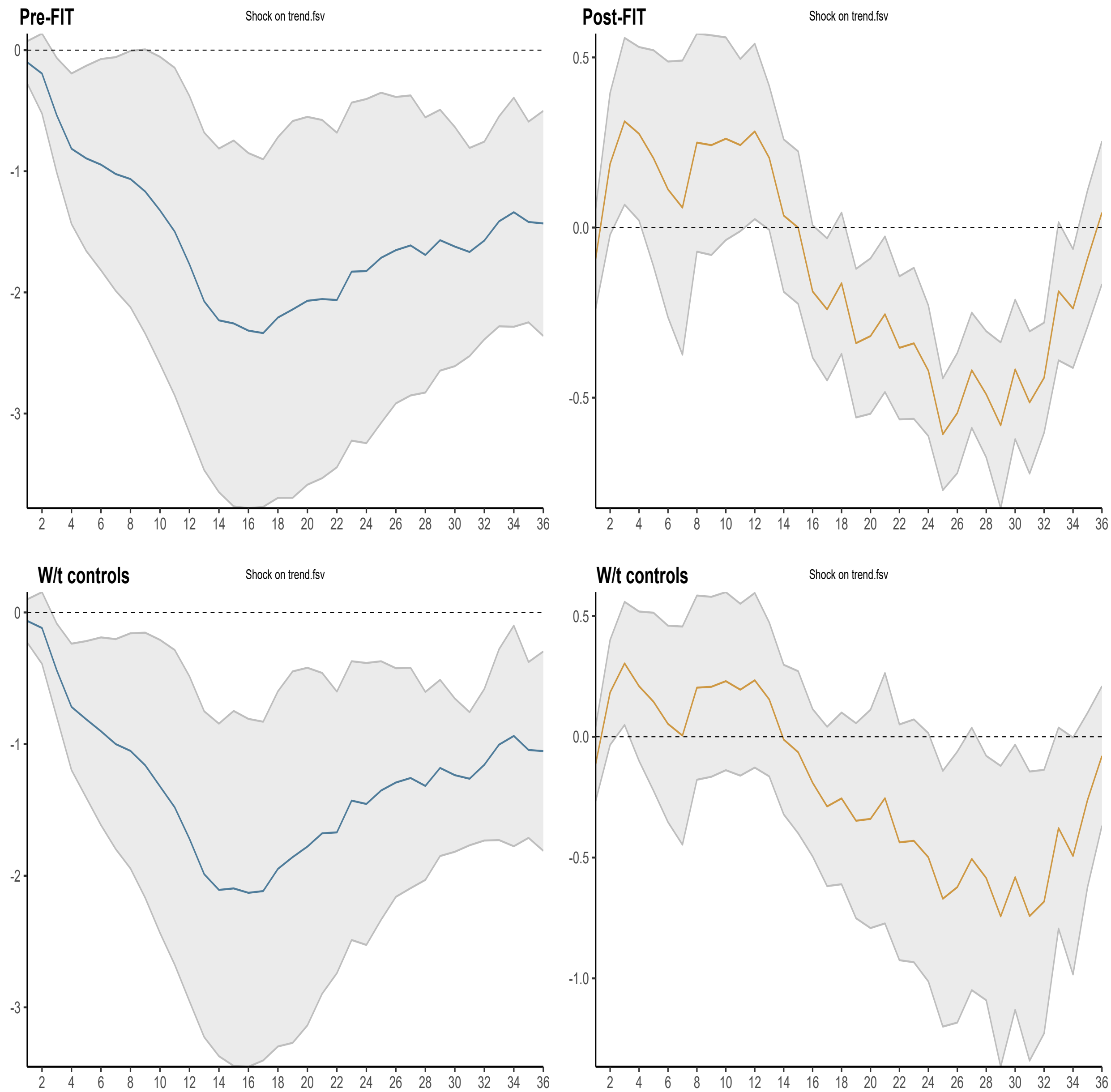

Figure 9: State-dependent Impulse Responses of DFM-based Long-run Inflation Expectations to Inflation Sentiment Shock

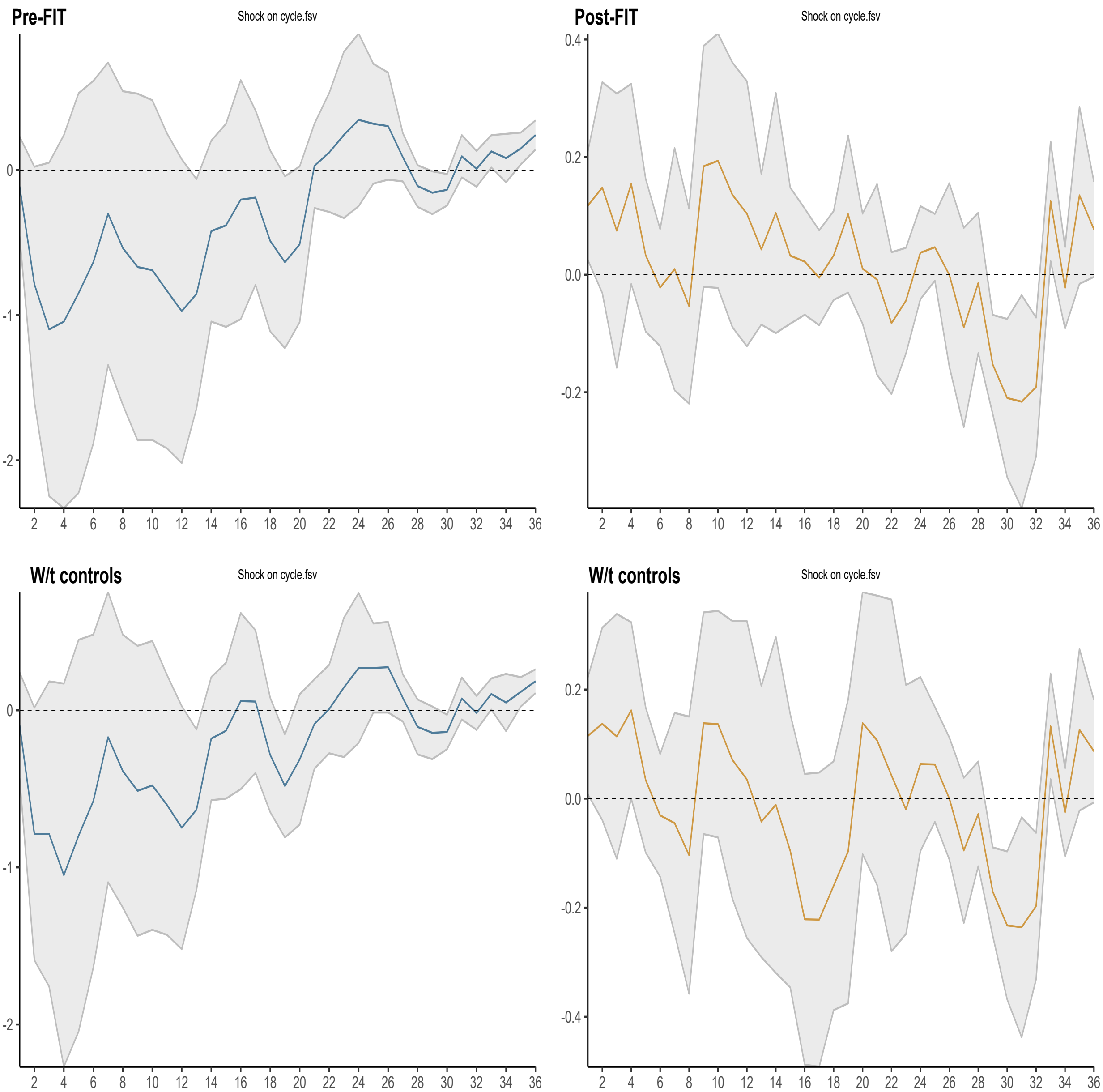

Figure 10: State-dependent Impulse Responses of DFM-based Short-run Inflation Expectations to Inflation Sentiment Shock

Table 1: Granger Causality Test: CPI Headline Inflation and Inflation Sentiment Index

hypothesis	*Lags* 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.

Table 2: 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

Table 3: Sensitivity of SPF Inflation Expectations to Inflation[1]

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

[1] SPF_4Q is 4-quarter ahead median inflation forecast and SPF_1Q is 1-quarter ahead median inflation forecast from SPF survey.

Table 4: Estimated Hyperparameters from the State Space Model

AR Parameters	**SD**	**Loading Parameters**	**Intercepts**		
β	0.93	σ_τ	0.17	μ^τ	-0.01
ϕ_1	0.67	σ_c	0.17		
ϕ_2	0.65	σ_1	0.46	δ_1	1
ϕ_3	0.65	σ_2	0.39	δ_2	0.34
ϕ_4	0.83	σ_3	0.27	δ_3	0.05
ϕ_5	0.70	σ_4	0.18	δ_4	0.05
ϕ_6	0.57	σ_5	0.17	δ_5	0.18
ϕ_7	0.71	σ_6	0.43	δ_6	0.93
ϕ_8	0.80	σ_7	0.23	δ_7	0.39
ϕ_9	0.65	σ_8	0.39	δ_8	0.34
ϕ_{10}	0.71	σ_9	0.21	δ_9	0.35
ϕ_{11}	0.46	σ_{10}	0.24	δ_{10}	1.56
ϕ_{12}	0.49	σ_{11}	0.21	δ_{11}	-0.20
ϕ_{13}	0.50	σ_{12}	0.20	δ_{12}	0.38
ϕ_{14}	0.73	σ_{13}	0.24	δ_{13}	0.31
		σ_{14}	0.24	δ_{14}	0.11