Forecasting Core Inflation in India: A Four-Step Approach

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Abstract

We propose a novel approach to forecasting core inflation in India, whose average contribution to headline inflation has been about 55 percent since January 2016. Our approach involves using the dis-aggregated components of core inflation, as well as the construction of a demand index using high frequency (HF) indicators. We find that individually forecasting and then aggregating core CPI components improves the short-term forecasting accuracy of core inflation. However, forecasting aggregate core inflation directly is more effective for longer horizons. We estimate a demand index using high frequency indicators. We find that the inclusion of the demand index and other co-variates enhances forecasting efficacy by capturing demand-side factors specific to the Indian economy. We also find that an accurate specification of the dis-aggregate components model contributes to maximizing prediction accuracy.

Keywords: Inflation Forecasting in EMEs, Core Inflation, State-Space Models, Dynamic Factor Models, Macroeconomic Management, Inflation Targeting.

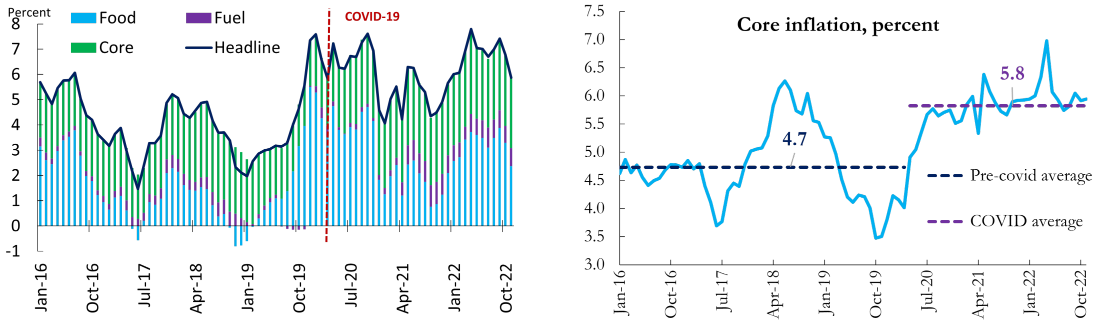
JEL Code: C53, E31, E37, E52

1 Introduction

Inflation forecasting plays a pivotal role in guiding central bank policy decisions, promoting economic stability, and shaping the decisions of businesses and households. The adoption of a flexible inflation-targeting (FIT) framework by the Reserve Bank of India (RBI) in 2016 constitutes an important step towards enhancing monetary policy effectiveness (Ahmed and Ghate (2022), Eichengreen, Gupta, and Choudhary (2020)). Under FIT, the RBI's policy decisions and communications rely heavily on accurate predictions of inflation projections. Achieving an accurate forecast of inflation becomes crucial not only for the central bank but also for businesses and households throughout the wider economy. Moreover, gaining insights into the composition of inflation is vital for effective policy formulation and forecasting accuracy. This research paper aims to contribute to the existing literature on forecasting inflation by focusing on forecasting core inflation in India. Our paper's findings contribute to the existing body of research on inflation forecasting in emerging market economies and provides useful insights for policymakers, researchers, and market participants seeking to make informed decisions in an uncertain economic environment.

Why core inflation? First, core inflation, excluding the volatile components of food and fuel, constitutes a substantial portion (approximately 47 percent) of headline inflation in India. Second, as can be seen from Figure 1, since 2016, core inflation has consistently contributed an average of 2.4 percentage points to headline inflation, accounting for around 55 percent of the overall contribution on average. Third, while the nominal anchor in FIT in India is headline CPI (Consumer Price Inflation), it is widely recognized that core inflation proxies for demand side inflation in the economy (see RBI (2014)). Fourth, from an average and relatively stable value of 4.7 percent during January 2016 - March 2020, core inflation's average increased to 5.8 percent between March 2020 and October 2022 during COVID. Fifth, there is a large literature in the Indian context that shows that headline inflation converges to core inflation (Goyal and Parab (2020), Blagrave and Lian (2020)), suggesting its significant role in shaping headline inflation dynamics.

To forecast core CPI inflation in India, we devise a comprehensive four-step procedure. First, following Sharma and Padhi (2020) we carefully identify and construct a demand index based on high-frequency indicators which have proven to be effective in forecasting core inflation. Extending Sharma and Padhi (ibid.) however, we estimate the demand index using two approaches: the EM algorithm and a Bayesian approach. Our motivation for estimating a demand index is to bypass well-known problems (e.g., time lag in RGDP data releases) associated



(a) Contribution to headline inflation

(b) Average Core inflation rate, percent

Figure 1: The Average Contribution of Core Inflation: Jan 2016-Oct 2022
Source: RBI, Authors' Calculations.

with the output gap as a proxy for demand side pressures in the economy.[5]

Second, while we forecast aggregate core inflation by fitting a uni-variate ARIMAX model that encompasses food, fuel, and core inflation, we also look at individual components of core inflation by fitting separate ARIMAX models for each component and then combine the dis-aggregated forecasts. This is a bottoms-up approach. It enables us to capture the unique dynamics of individual core inflation components as well as their individual contributions to aggregate core inflation. We then augment both the aggregate and dis-aggregate forecasts with other co-variates: the demand index based on high frequency indicators, a proxy for global supply chain dynamics, oil prices, and the Real Effective Exchange rate (REER). As became apparent during COVID-19, inclusion of both global supply chain dynamics and oil prices allows for supply side disturbances in impacting core inflation.

Third, we construct the aggregate core index by applying the forecasts of quarter-on-quarter inflation rates to the index value at the commencement of the forecast horizon.

Finally, and fourth, we compute the year-on-year growth rate of the predicted aggregate core index obtained in the previous step. This approach allows us to factor in base effects, which play a substantial role in India's inflation dynamics

While recent advancements in data availability and computing power have revolutionized the field of economic forecasting, our approach fills several gaps in the literature.[6] For instance, Jose et al. (2021) present a comparative analysis of var-

[5]In India, output gap measures are based on quarterly real GDP (RGDP) data and rely on national accounts data. Quarterly RGDP releases happen approximately two months after the reference quarter.

[6]These advancements allow the usage of a large set of predictors, allow for exploring non-linear features, and use modern ML (machine learning) methods (see Medeiros et al. (2021) and Kohlscheen (2021)). Notably, factor models utilizing high-frequency macroeconomic datasets have emerged as effective tools for predicting demand and capturing intricate economic relationships (Jarociński and Lenza (2018)).

ious models in forecasting CPI headline inflation in India. The results indicate that the SARIMA model outperforms the Phillips curve variant for one-quarter ahead forecasts. However, for longer horizons (4-quarter ahead) and core inflation, the Phillips curve-based model exhibits superior predictive performance. Notably, integrating Phillips curve-based models into dis-aggregate inflation forecasts enhances their effectiveness when compared to aggregate forecasts. However, their findings are based on an examination of pre-COVID data and solely rely on an HP-filtered output gap measure. They do not include a comprehensive set of high-frequency data, which could potentially be more accurate in predicting core inflation.

Sharma and Padhi (2020) contribute to the understanding of the significance of demand in inflation forecasting by incorporating the Phillips curve equation into a Bayesian Dynamic Factor (DF) state space model.[7] Their study shows that the inclusion of a demand index derived from ten high-frequency indicators, capturing macroeconomic activity, significantly enhances forecasting accuracy. This innovative approach enables the extraction of the output gap, a critical indicator that provides valuable information on inflationary pressures. However, their study does not examine the relative efficacy of forecasting performance when conducting component-wise forecasts as compared to aggregate core index forecasts. In addition to constructing a demand index using the EM algorithm, we also construct the demand index using a Bayesian MCMC algorithm. We also allow for the staggered release of data, aspects not considered in Sharma and Padhi (ibid.).

Our approach to forecasting core-inflation by combining dis-aggregate forecasts is motivated by two reasons. First, combining dis-aggregate forecasts allows for a more nuanced consideration of the unique dynamic properties exhibited by each component. Second, it holds the potential to mitigate forecast errors through partial error cancellation, as highlighted by Clements and D. F. Hendry (2002). However, there are problems associated with this approach. Misspecification of dis-aggregate models may lead to under-performance, as cautioned by Grunfeld and Griliches (1960). Further, anticipated error cancellation may not materialize if unexpected shocks affect the dis-aggregate variables in a correlated manner. In the broader literature, empirical evidence on the effectiveness of combining dis-aggregated forecasts presents a mixed picture. For instance, Hubrich (2005) finds limited improvement in year-on-year inflation forecasts over a 12-month horizon by aggregating consumer price inflation forecasts by component in the Euro area. In contrast, D. Hendry and Hubrich (2011) suggests leveraging dis-aggregate informa-

[7] Previous studies by Patra and Kapur (2012) utilizing WPI inflation data and Behera, Wahi, and Kapur (2017) employing CPI data further reinforce the relevance of the Phillips curve hypothesis within the Indian context.

tion to enhance aggregate forecasts without explicitly combining the dis-aggregate forecasts. Within the Indian context, Chaudhuri and Bhadhuri (2019) find that dis-aggregate data can lead to improvements in forecast accuracy for WPI inflation compared to aggregate forecasts, up to a certain level of dis-aggregation. We find that there is a trade-off. Dis-aggregating forecasts improves relative forecasting efficacy in shorter time horizons (one-two quarters). Aggregate forecasts have a higher relative efficacy in longer time horizons (three-four quarters).

In sum, our paper provides a new approach and new insights into forecasting core inflation in a large emerging market economy (EME) such as India. Given the methodological focus of our paper, our approach is general enough to be relevant for both other EMEs and other developed economies (DEs). Our main findings highlight the significance of incorporating demand in inflation forecasting in a robust way, as well as highlighting the relative merits of combining dis-aggregate forecasts in forecasting aggregate core inflation.

2 A New Approach to Forecasting Core Inflation

To forecast core CPI inflation in India, we devise a four-step procedure. Using quarterly data in India between March 2015 - March 2020, Figure 2 shows that core inflation and the output gap in India co-move quite strongly.[8] One significant limitation of the conventional output gap measure is the availability of data with a time lag. Therefore, in the first step, following Sharma and Padhi (2020), we construct a demand index based on select high frequency indicators.[9] As in Sharma and Padhi (ibid.), we combine a dynamic factor model (DFM) with a Phillips curve equation to estimate the measure of economic slack and capture latent demand dynamics. Out of several high frequency indicators, we pick those that are relevant for affecting the demand side of the economy.[10]Our choice of high frequency indicators include: components of the index of industrial production (IIP), automobile sales, credit, petroleum consumption among others.[11] In addition, we recognize the potential impact of global supply chain dynamics on India's core inflation. Thus, we incorporate the supply chain pressure index (GSCPI) released by the Federal Reserve Bank of New York in our forecasting analysis. This index provides a valuable gauge of cross-border transportation costs and incorpo-

[8]The output gap has been constructed using the HP filter.

[9]These authors show that their demand index has a superior performance in predicting core inflation compared to other slack measures, such as the output-gap and capacity utilization.

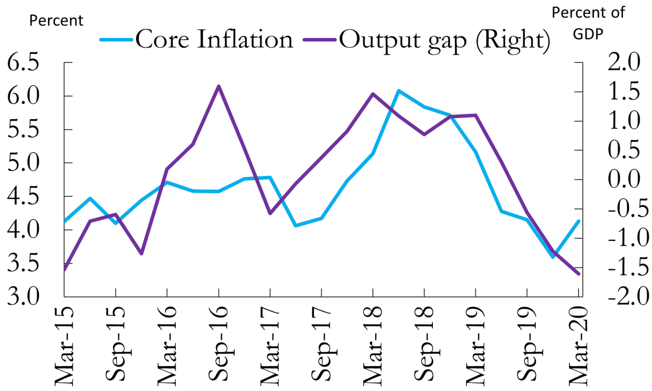
[10]We tried estimating the demand index using several additional indicators, and clustering them using Principal Components Analysis (PCA). Our results don't change substantially.

[11]High frequency indicators are obtained from CEIC, MOSPI, and the RBI. See Table 3 for details.

rates manufacturer surveys, enabling us to gain insights into India's core inflation dynamics.

The final demand index is based on ten key indicators and constructed using a state-space model. The dynamic factor model extracts a common factor from a range of high-frequency indicators, which allows us to capture underlying trends.[12] Simultaneously, the Phillips curve equation ensures that this common factor contains valuable information about inflation dynamics, enabling us to incorporate inflation-related insights into the demand index. To estimate the model parameters, we employ both the EM algorithm and the MCMC algorithm, which follows a Bayesian approach. The above approach allows us to capture the intricate dynamics between demand-side indicators and core inflation in a rigorous way.

Figure 2: Co-movement of Core inflation and the Output Gap in India



Source: RBI, MOSPI, Authors' calculations.

More formally, let Y_{it} represent the high-frequency indicator i at time t, let X_t denote the latent demand variable[13], let λ_i represent the loading factor, and ϵ_{it}^Y the error term. The dynamics of Y_{it} follows

$$Y_{it} = \lambda_i X_t + \epsilon_{it}^Y, \quad i = 1, ..., K \tag{1}$$

where the shocks to high-frequency indicators follow an auto-regressive (AR) process, where ρ_i captures the persistence of shocks and e_{it} is the white noise error term.

[12]In simpler terms, the dynamic factor model captures the shared underlying trend present in multiple high-frequency indicators, providing insights into the common driving forces behind economic fluctuations.

[13]Since our goal is to proxy for the output gap, we consider the cyclical component of all high-frequency indicators extracted using the HP-filter.

We assume that the unobserved demand variable, X_t, evolves according to

$$X_t = \phi_1 X_{t-1} + \phi_2 X_{t-2} + \epsilon_t^X, \quad \epsilon_t^X \sim i.i.d.\,\mathcal{N}(0,\, \sigma_X^2) \tag{2}$$

where the dynamics of X_t incorporate lagged effects with coefficients ϕ_1 and ϕ_2, and an error term ϵ_t^X which follows a normal distribution,

$$\epsilon_{it}^Y = \rho_i \epsilon_{i,t-1}^Y + e_{it}, \quad e_{it} \sim i.i.d.\,\mathcal{N}(0,\, \sigma_e^2), \quad i = 1, ..., K \tag{3}$$

Our specification of the the Phillips curve is standard and follows Sharma and Padhi (2020). Equation (4) below relates core inflation π_t^{core} to trend inflation π_t^{trend}, the demand variable X_t, and an error term ϵ_t^π, incorporating coefficients β_1 and β_2.

$$\pi_t^{core} = \pi_t^{trend} + \beta_1 X_t + \beta_2 X_{t-1} + \epsilon_t^\pi \tag{4}$$

Trend inflation dynamics follow a random walk without drift, where ζ_t represents the random shock term,

$$\pi_t^{trend} = \pi_{t-1}^{trend} + \zeta_t, \quad \zeta_t \sim i.i.d.\,\mathcal{N}(0,\, \sigma_\zeta^2) \tag{5}$$

The shock to core inflation follows an AR(1) process, where $0 < \gamma < 1$ captures the persistence of shocks and ν_t is the white noise error term.

$$\epsilon_t^\pi = \gamma \epsilon_{t-1}^\pi + \nu_t, \quad \nu_t \sim i.i.d.\,\mathcal{N}(0,\, \sigma_\nu^2) \tag{6}$$

Equations (1)-(6) represent the interplay between high-frequency indicators, latent demand dynamics, and inflation dynamics. The underlying dynamics described by the above system of equations can be captured using a state-space representation, as detailed in Appendix C. The Kalman Filter is widely recognized for its optimality in state-space estimation for known parameter state space models. It serves as a powerful tool to solve this model. The state-space model allows us to gain insights into the unobserved states based on available observations.[14] However, since the parameters of the model are unknown, we use the Expectation-Maximization (EM) algorithm for their estimation.[15] This algorithm leverages the joint density of the observed states and observations to iteratively update and refine parameter estimates through a series of E-step and M-step it-

[14] The Kalman Filter algorithm has two essential steps: Time Update and Measurement Update. In the Time Update, we predict the observations using all available information up to time t-1. In the Measurement Update, after obtaining the actual observations at time t, we calculate the prediction error, which provides new information about the states beyond previous estimates. See Appendix C for details

[15] We also estimate the demand index using a Bayesian Markov Chain Monte Carlo (MCMC) algorithm for robustness.

erations (see Appendix D). The above constitutes the *first step* in the forecasting procedure.

In *Step 2*, we use two distinct approaches. First, we forecast the aggregate core inflation series by fitting a uni-variate ARIMAX or VAR model that encompasses food, fuel, and core inflation.[16] This approach captures closely overall core inflation dynamics. Our focus lies in predicting core inflation π_t for the period $t+h$, leveraging historical patterns of π_t along with a set of predictors, $\mathbf{X_t}$. The predictive model can be expressed as:

$$\hat{\pi}_{t+h} = a + b(L)\pi_t + \mathbf{X_t} + c(L)\epsilon_t \tag{7}$$

In Equation (7), a, $b(L)$, and $c(L)$ are estimated parameters.[17] We employ Ordinary Least Squares (OLS) to estimate these parameters on recursive samples spanning from 2012:Q3 to 2019:Q4 through 2012:Q3 to 2021:Q3. The accuracy of our predictions is then assessed using the Root Mean Square Error (RMSE) across forecast horizons of one, two, three, and four quarters ahead. We dis-aggregate the components of core inflation by fitting separate ARIMAX models as in equation (7) for each component of core inflation and subsequently combine the dis-aggregated forecasts.[18] The aggregation is done by taking the weighted average of the components, where officially assigned weights are used.[19] This approach enables us to capture the unique dynamics of individual components and their respective contributions to core inflation.[20]

In *Step 3* we directly forecast the aggregate core inflation index. To achieve this, we apply the predicted quarter-on-quarter growth rate, derived from Step 2 of our methodology, to the initial index value at the beginning of the forecast horizon. This allows us to obtain the predicted index values for the aggregate core component. In the dis-aggregate framework, we focus on forecasting the individual components of core inflation. We apply the predicted quarter-on-quarter growth rate forecasts from Step 2 to each component's index value, thereby obtaining forecasts for their respective index values. To obtain the predicted core index value, we combine these individual component forecasts using official weights that

[16] A VAR framework cannot be used to capture core component interactions due to limited observations and numerous parameters to estimate.

[17] The lag length of lag operator polynomials, $b(L)$, and $c(L)$, is determined using information criteria.

[18] The core inflation measure in this study includes the following sub-components: Housing, Transport and Communication, Clothing and Footwear, Health, Education, Personal Care and Effects, Household Goods and Services, Pan, Tobacco and Intoxicants, and Recreation and Amusement. Summary statistics for these sub-components can be found in Appendix A.

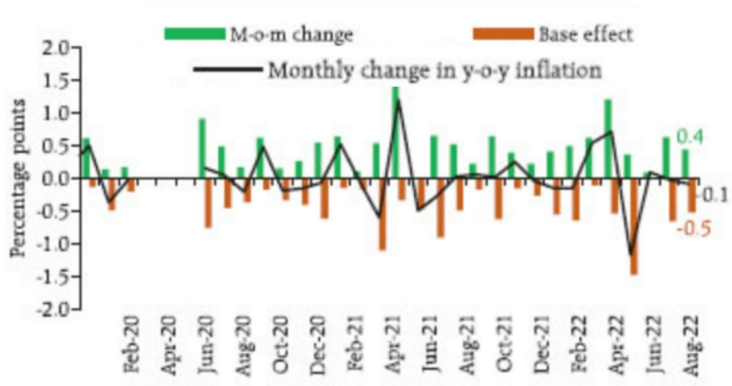
[19] See Appendix A.

[20] In predictive modeling, the focus is on association rather than causation. The criteria for choosing predictors are quality of the association between the predictors and the response, data quality, and the availability of predictors at the time of prediction. See Shmueli (2010).

reflect the relative importance of each component in the overall core index.

Finally, in *Step 4* we compute the year-on-year growth rate of the predicted aggregate core index obtained in Step 3. This approach allows us to factor in base effects, which play a substantial role in India's inflation dynamics. Figure 3 shows that in recent years, the base effects in monthly changes in year-on-year inflation are quite large.

Figure 3: Core inflation: Base Effects vs. Sequential Momentum



Source: Monetary Policy Report, Sep 2022, RBI.

Figure 4 Diagramatic Summary of the Four-Step Procedure.

3 Description of Data

We focus on core consumer price inflation and its components, with data available monthly from January 2011 to November 2022. This extended time frame allows us to capture a comprehensive view of inflation dynamics and study any potential changes over the years.

To enhance the forecasting accuracy of core consumer price inflation, we include a set of relevant predictor variables. These predictors encompass various aspects of the economy, both domestic and global, that are expected to have an impact on inflation dynamics. Additionally, we utilize various predictors, including high-frequency macroeconomic data, a global supply chain pressure index (GSCPI), crude oil prices (Indian basket), and the real effective exchange rate (REER) obtained from the Reserve Bank of India (RBI) and the Federal Reserve Bank of New York (FED NY). The predictors used in our analysis include:

- *Monthly Macroeconomic Data:* We consider a range of high-frequency indicators such as the Index of Industrial Production (IIP) and its components, non-food credit, and other relevant variables. These indicators provide insights into the overall economic activity and can serve as leading indicators for inflation.

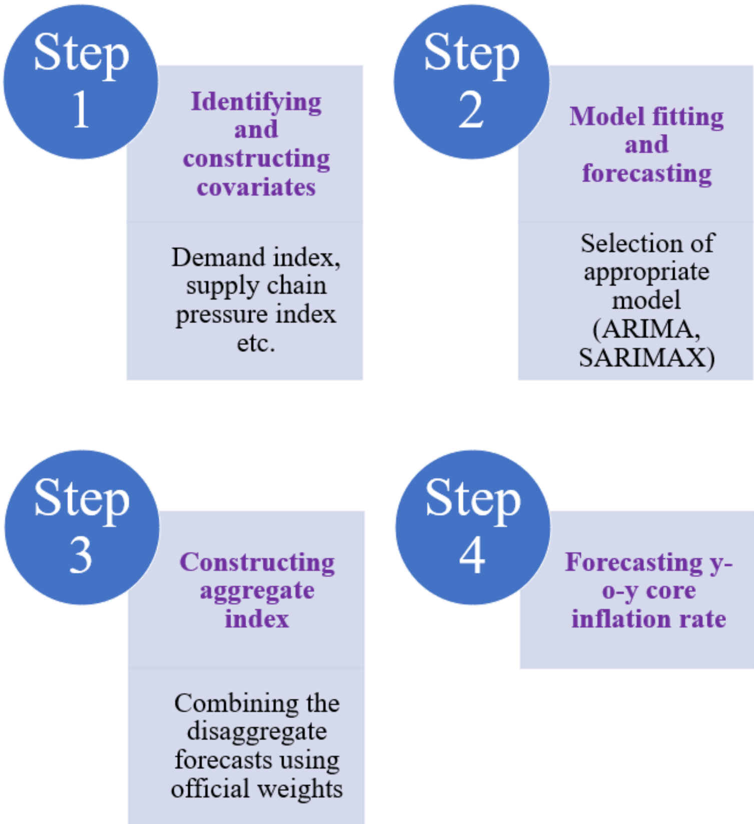


Figure 4: A Four Step Approach

- *Global Supply Chain Pressure Index (GSCPI):* Obtained from the Federal Reserve Bank of New York FED NY (2023), the GSCPI reflects the pressures experienced by global supply chains. Global transportation expenses are evaluated using information from the Baltic Dry Index and the Harpex index, along with airfreight cost indicators from the U.S. Bureau of Labor Statistics. The GSCPI also integrates supply chain data from PMI surveys, focusing on manufacturing firms across interconnected economies: China, Eurozone, Japan, South Korea, Taiwan, the UK, and the US. Changes in global supply chains can influence the availability and pricing of goods, which can impact domestic inflation.

- *Crude Oil Prices (Indian Basket):* Crude oil prices are known to have a significant influence on inflation, particularly in oil-importing countries like India. We consider the Indian basket of crude oil prices as a predictor in our analysis.

- *Real Effective Exchange Rate (REER):* The REER, sourced from the Reserve Bank of India (RBI), captures the relative strength of a country's currency against a basket of currencies of its major trading partners. Fluctuations in the REER can affect the prices of imported goods and consequently impact domestic inflation.

We aggregate the data to a quarterly frequency as the official reporting (by the Monetary Policy Committee) requires quarterly forecast trajectories. To ensure stationarity and to account for cyclical components, we apply specific transformations to the data. For the High-Frequency (HF) data (used to construct the demand index), we take the first difference of the log-levels of the indicators and then extract the cyclical component using an HP filter. This transformation allows us to remove any trends and isolate the cyclical component for better forecasting accuracy. For the monthly Demand Index and GSCPI, we average them at a quarterly frequency. This averaging process helps to reduce noise and capture the underlying trends at a more manageable interval for forecasting purposes. For core inflation and its components, we average them at a quarterly frequency. Subsequently, we take the first difference of the log-levels of these variables. This transformation helps address any non-stationarity and focuses on capturing changes in the variables' growth rates.

Our analysis covers the period from the third quarter of 2012 (2012:Q3) to the third quarter of 2022 (2022:Q3). Within this sample period, we employ a recursive training approach to build our forecasting models. Specifically, we split the sample period into two segments: the training sample and the forecasting period. The training sample extends from the third quarter of 2012 (2012:Q3) to the fourth quarter of 2019 (2019:Q4). This extended period allows us to capture varying economic conditions and their effects on inflation dynamics. We employ a recursive approach by using the training sample to estimate our forecasting models repeatedly, updating the estimates at each subsequent quarter.

4 Main Results

4.1 Demand Index

This sub-section presents the findings of the demand index constructed using high-frequency indicators, utilizing two different algorithms: the Expectation-Maximization (EM) algorithm and for robustness, the Bayesian Markov Chain Monte Carlo (MCMC) algorithm[21].

First, using the EM Algorithm, we find a strong correlation between the derived demand index and the actual output gap measure, as can be seen in Figure 5.[22]The

[21] These algorithms are implemented in R; for package details, please see the Appendix D and Appendix F.

[22] The HP filter is applied to quarterly real GDP data to obtain the output gap measure.

positive correlation is approximately 56 percent, signifying the demand index's proficiency in capturing fluctuations in the economy's output level. Remarkably, when we include the COVID-19 period, this correlation strengthens significantly, exceeding 90 percent. These findings underscore the demand index's ability to capture the disruptive effects of COVID-19 on economic activity.

Second, when we employ the Bayesian MCMC algorithm to construct an alternative derived demand index, this yields similar results. Our final analysis demonstrates a strong correlation between the Bayesian-derived demand index and the actual output gap measure.[23] This can be seen in Figure 5. This correlation strengthens our confidence in the demand index's capability to effectively capture economic fluctuations and aligns with our earlier findings based on the EM algorithm. Consequently, the demand index - in lieu of the output gap - exhibits potential for predicting core inflation.

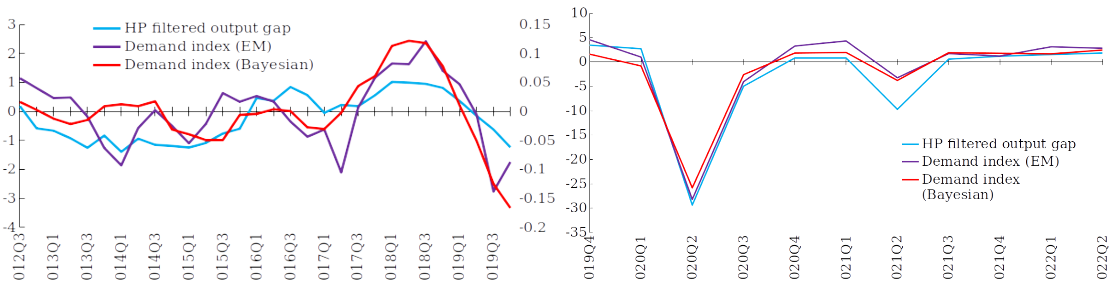


Figure 5: Demand Index and Movements in the Real GDP cycle
Source: Authors' calculations, MOSPI.

For the Bayesian MCMC algorithm, we also conduct sensitivity checks by employing different priors to ensure the robustness and reliability of the Bayesian-derived demand index (see Section 5.1).

4.2 Forecasting Performance

We now examine the forecasting performance of selected models for predicting core inflation, with a focus on the utilization of different co-variates, including the derived demand index.

Our baseline model is a simple auto-regressive integrated moving average (ARIMA) model, with the order determined using information criteria. We consider two distinct approaches: aggregate forecasting, where the model is directly fitted to core

[23]The correlation coefficient between the Bayesian demand index and the output gap measure is 96.63 percent, whereas the correlation coefficient between the Bayesian demand index and the EM-based demand index is 96.47 percent.

inflation, and dis-aggregated forecasting, where the components of core inflation are forecasted individually and then aggregated.

The results reveal interesting trade-offs between the two forecasting approaches (Table 1). For 3-4 quarter ahead predictions, aggregate forecasting demonstrates lower relative Root Mean Squared Error (RMSE) values, indicating better accuracy in capturing longer-term trends. Conversely, for 1-2 quarter ahead predictions, dis-aggregated forecasting outperforms, exhibiting lower RMSE values and showcases superior short-term predictive ability. Within the aggregate forecasting framework, the inclusion of co-variates such as the EM-derived demand index (D10), Bayesian-derived demand index (BD10), Hodrick-Prescott filtered output gap (HP gap), and Global Supply Chain Pressure index (SS) yields mixed results. While incorporating D10 improves forecasting accuracy across all horizons, the addition of BD10, HP gap, or SS does not consistently enhance performance. When combining dis-aggregated forecasts, the relative RMSE values generally increase compared to aggregate forecasting, indicating reduced accuracy. However, specific combinations, such as ARIMA + D10 + SS and ARIMA + BD10 + SS, demonstrate lower relative RMSE values for 1-2 quarter ahead predictions, indicating improved short-term accuracy compared to aggregate forecasting. Furthermore, incorporating additional variables, such as oil prices (Oil), in the dis-aggregated forecasting framework leads to mixed results. ARIMA + D10 + SS + Oil exhibits improved accuracy for 1-2 quarter ahead predictions, while ARIMA + BD10 + SS + Oil shows improved accuracy for 4-quarter ahead predictions.[24]

Considering separate choices of variables for the "Transport and Communication" (T & C) component within dis-aggregate forecasts, we observe varying levels of forecasting accuracy. Inclusion of co-variates such as D10, SS, the Real Effective Exchange Rate (REER), and Oil leads to lower relative RMSE values, indicating improved accuracy across different forecast horizons.

The dis-aggregate model's superiority over the aggregate model in short term forecasting can be attributed to two factors. First, it achieves a better model fit, resulting in lower individual RMSEs for component predictions. Secondly, it benefits from the cancellation of forecasting errors due to negative residual correlations among these components. Both help improve forecast efficiency in the short term forecasts. To validate this, we examine a dis-aggregate model that incorporates demand indices for all components but also includes crude oil prices

[24]We also tried substituting some variables (passenger traffic, SCB Credit, Tractor Sales) in the demand index with broad money $M3$. We find that incorporating $M3$ helps in getting diminished relative RMSE values, suggesting that liquidity in the economy holds a more robust correlation or explanatory capacity in predicting core inflation, when compared to the variables it replaces. However, replacing out IIP with $M3$ worsens forecast accuracy suggesting that the result is not robust. See Appendix E.

Table 1: Relative RMSE of n-quarter ahead forecasts

A. Aggregate forecasting				
Model	1-quarter	2-quarter	3-quarter	4-quarter
ARIMA	1.00	1.00	1.00	1.00
ARIMA + D10	0.94	0.94	0.76	0.50
ARIMA + BD10	1.14	1.24	1.20	1.02
ARIMA + HP gap	1.02	1.11	1.03	0.92
ARIMA + SS	0.94	1.24	1.37	1.23
ARIMA + D10 + SS	1.03	1.18	1.13	1.10
ARIMA + BD10 + SS	1.12	1.30	1.25	1.11
B. Combination of dis-aggregate forecasts				
B1. Common model for all components				
Model	1-quarter	2-quarter	3-quarter	4-quarter
ARIMA	1.38	1.60	1.58	1.67
ARIMA + D10	1.22	1.39	1.31	1.24
ARIMA + BD10	1.24	1.62	1.66	1.71
ARIMA + HP gap	1.16	1.16	1.18	1.20
ARIMA + SS	1.00	1.30	1.33	1.35
ARIMA + D10 + SS	0.99	1.22	1.20	1.17
ARIMA + BD10 + SS	0.83	1.19	1.35	1.36
ARIMA + D10 + SS + Oil	1.05	1.45	1.47	1.47
ARIMA + BD10 + SS + Oil	0.91	1.25	1.31	1.24
B2. Distinct model for T & C				
Model ARIMA + D10 + SS + REER+ Fuel	1-quarter	2-quarter	3-quarter	4-quarter
T & C» D10 + SS + REER + Oil	0.62	0.99	1.23	1.23
T & C» D10 + REER + Oil	0.90	1.06	1.14	1.08
T & C» D10 + Oil	0.90	1.15	1.24	1.24
T & C» REER + Oil	0.81	1.21	1.57	1.59

Note: This table provides relative RMSE values, with the RMSE from the ARIMA model in the aggregate forecasting framework serving as the baseline. It is important to note that the baseline value varies for each forecast horizon. This enables a meaningful comparison between different models within a specific forecast horizon.

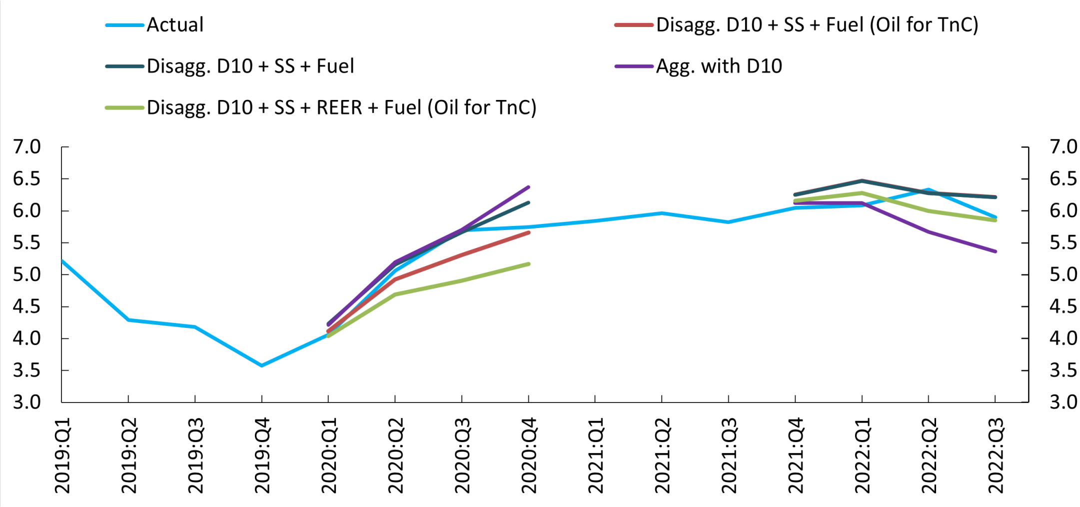


Figure 6: Actual vs. Out-of-sample forecasts
Note: Vertical axis shows core CPI inflation rate.
Source: Authors' estimates, MOSPI.

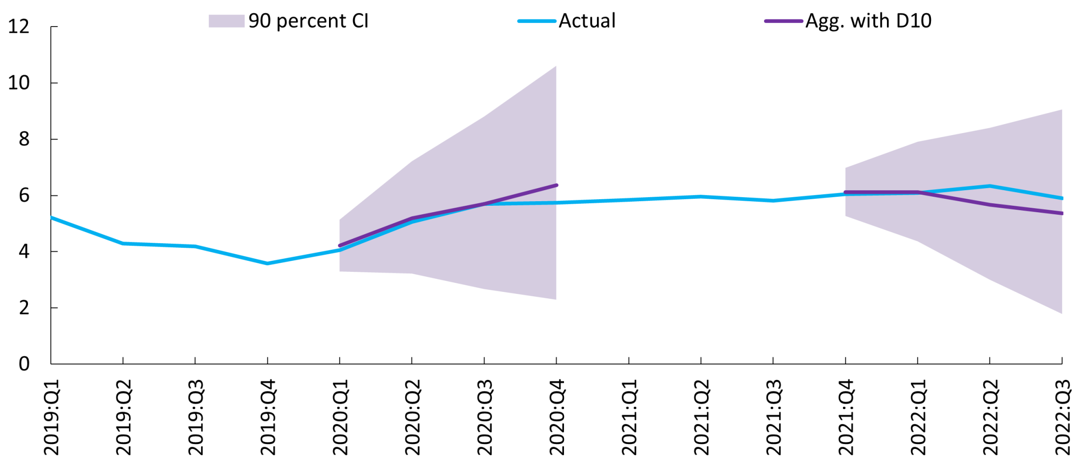


Figure 7: Out-of-sample forecasts with confidence band
Note: Vertical axis shows the Core Inflation Rate.
Source: Authors' estimates, MOSPI.

in transport and communication. We find that in the short term (1-2 quarters), negative correlations between forecasting errors help reduce the overall RMSE. However, in the long term (3-4 quarters), errors for individual predictions increase nearly fourfold compared to the short term, and are much higher compared to predictions based on the aggregate model. This suggests that the demand index doesn't consistently explain inflationary pressures across components, possibly due to variations in supply and demand imbalances among core components.[25]

Our findings highlight the importance of selecting appropriate co-variates and considering aggregate versus dis-aggregated forecasting approaches for specific forecast horizons and components. Figure 6 displays the comparison of the actual inflation rate with out-of-sample predictions from different models, while Figure 7 includes a 90 percent confidence band around the predicted inflation values.

4.2.1 2-year ahead forecasting

The Reserve Bank of India is responsible for providing reliable and accurate inflation forecasts, typically focused on a 2-year horizon. Therefore, in order to evaluate the resilience and reliability of 2-year ahead projections, an additional analysis incorporating an 8-quarter ahead forecast becomes relevant. Our analysis incorporates an 8-quarter ahead forecasting as a robustness check to validate the reliability of our findings based on the 4-quarter predictions. The results, presented in Appendix G.2, highlight that our key messages and insights remain consistent and robust across both forecast horizons. Notably, the inclusion of additional variables such as the demand index consistently improves forecast accuracy, reinforcing the significance of these factors in driving better predictions. Furthermore, the distinct models for different components (as illustrated in the case of "Transport and Communication") demonstrate promising results when incorporating other explanatory variables like the demand index, supply chain pressure index, and exchange rates.

5 Robustness

5.1 Sensitivity to different prior distributions

The robustness of the derived demand index (using the Bayesian approach) to different assumptions on priors is crucial. The results, as seen by the relative RMSE values in Table 2, suggest that our derived demand index remains robust to changes in prior distributions.

[25] We don't include these results due to space constraints. Details are available from the authors upon request.

Table 2: Relative RMSE for Different Priors on Parameters

	Q1	Q2	Q3	Q4
Standard priors	1	1	1	1
Loading factor as Beta instead of Normal	0.9988	0.9997	1.0004	1.0001
Demand index coeff. as Beta instead of Normal	0.9999	1.0004	1.0012	1.0010
Phillips curve coeff. as Normal instead of Beta	1.0021	1.0027	1.0037	1.0035

Note: Standard prior case is treated as baseline for the construction of relative RMSE.

In particular, altering the priors for the loading factor and the demand index coefficient (by replacing the Normal priors with Beta priors) leads to slight improvements in accuracy, reflected in the decreased relative RMSE values. These findings indicate that the model's performance in capturing the impact of these variables are robust across different prior assumptions. Furthermore, the comparison between the Normal and Beta priors for the Phillips curve coefficient reveals a slightly increased relative RMSE when using the Normal prior. Although this suggests that the Beta prior might be more suitable for this coefficient, the overall impact on the model's robustness is minimal.

5.2 Staggered Availability of Data

One potential criticism of the derived demand index is having uneven availability of high-frequency data during the forecasting process. In practice, we may encounter situations where the HF indicators are not uniformly accessible at all points in time. For example, the availability of HF data at the beginning of a quarter may differ from that towards the end of the quarter, leading to incomplete information for forecasting inflation. To address this concern, we assess whether forecasting efficiency significantly varies due to the staggered availability of HF data. Specifically, we examine whether there are notable differences in the RMSE across different forecast horizons based on the information (HF data) available at the beginning of a quarter compared to the RMSE based on data available towards the end of the same quarter.

We examine the impact of staggered data availability on the forecasting efficiency using the ARIMA + BD10 model. Figure 8 shows the relative RMSE values for three scenarios: minimal information, partial information, and full information. These scenarios represent the availability of high-frequency (HF) data at different points in time within a quarter.[26] For the minimal information scenario, where only limited HF data is available at the beginning of the quarter, we observe higher relative RMSE values, indicating lower forecasting accuracy. No-

[26]This information is used to provide n quarter ahead forecasts. See Appendix H.

tably, the impact of limited data is more pronounced for shorter forecast horizons. The relative RMSE values for the 1 and 2 quarter ahead forecasts are approximately twice as high compared to the full information scenario. In the partial information scenario, where HF data becomes increasingly available towards the middle of the quarter,[27] we observe a decrease in relative RMSE values. However, the impact of data availability on forecast accuracy is still notable, especially for nearer forecast horizons. The relative RMSE values remain higher for the 1 and 2 quarter ahead forecasts compared to the full information scenario. Finally, in the full information scenario, all HF data from the entire quarter is available. In this case, the relative RMSE values are significantly lower across all forecast horizons, indicating the highest level of forecasting efficiency. The results suggest that the availability of HF data at different time points within a quarter can have a more significant impact on the accuracy of nearer horizon forecasts (1 and 2 quarters ahead) compared to forecasts further into the future (3 and 4 quarters ahead).

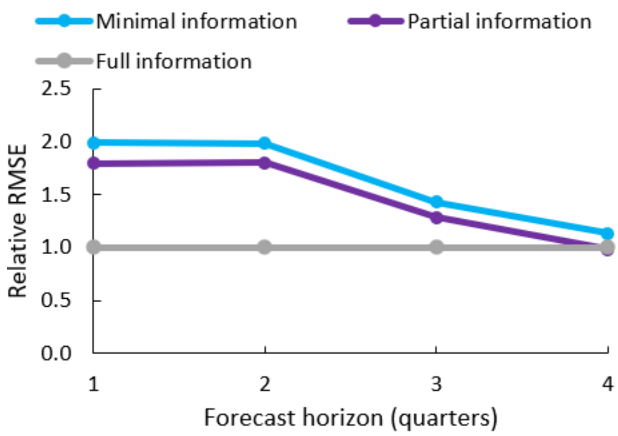


Figure 8: Incomplete HF Data and Forecast Accuracy
Note: Relative RMSE is with respect to the full information case corresponding to each forecast horizon. Source: Authors' estimates.

The analysis highlights two key factors. Firstly, a diverse set of high-frequency data significantly impacts forecasting accuracy. Secondly, timely availability of data provided by statistical agencies is crucial, particularly for shorter forecast horizons.

6 Conclusion

This paper examines different approaches to forecasting core inflation, specifically the forecasting of core CPI components and the use of a demand index derived from HF indicators. The findings of this study shed light on the efficacy of various

[27] Specifically, at the start of second month of the quarter.

approaches in both the short run (1-2 quarters ahead) and the long run (beyond 2 quarters).

The results indicate that when it comes to short-term forecasting, employing an approach that involves separately forecasting the core CPI components and then aggregating them leads to improved forecasting efficacy. This approach allows for a more precise understanding of the underlying dynamics within each component, thereby capturing short-term fluctuations more accurately. However, as the forecast horizon extends to the long run, directly forecasting the aggregate series proves to be more effective. This suggests that in the long run, the inter-relationship between the components become important, and their combined effect becomes more significant in forecasting efficacy. The inter-relationship among the components can stem from various sources, including common underlying factors, spillover effects, and transmission channels. For instance, changes in one component, such as energy prices, may have knock-on effects on other components, such as transportation costs or production expenses, leading to a ripple effect on overall inflation. By directly forecasting aggregate core inflation, these inter-dependencies get captured and this allows for a more comprehensive understanding of long-run inflation dynamics. Therefore, in the context of long-term forecasting, directly forecasting aggregate core inflation provides a more accurate representation of overall inflation behavior, considering the collective impact of core CPI components.

We show that the inclusion of a demand index, derived using HF indicators, enhances forecasting efficacy. The demand index provides valuable information regarding overall economic activity, which is crucial for understanding inflation dynamics. Incorporating this demand index into the forecasting model improves the accuracy of predictions by capturing the underlying demand-side factors that influence inflation.

Our paper highlights the importance of correctly specifying the components model when employing the "combination of dis-aggregate" approach. By employing an appropriate specification, this approach outperforms other forecasting methods. The accurate specification of the model enables a better understanding of the unique characteristics and relationships within each component, leading to more accurate predictions.

Overall, we demonstrate that forecasting core inflation requires a nuanced approach. Our paper's findings contribute to the existing body of research on inflation forecasting in emerging market economies and provides useful insights for policymakers, researchers, and market participants seeking to make informed decisions in an uncertain economic environment.

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Appendix

A Summary statistics

Table 3 lists various high-frequency indicators used in the construction of demand index.

Table 3: List of High-Frequency Indicators

Indicators	
Passenger vehicle sales	IIP general
Farm tractors sales	IIP consumer non-durable goods
Two-wheeler sales	Petroleum consumption
Air passenger traffic (domestic)	Crude steel production
Non-oil import	SCB Non-food credit

Table 4 presents statistics for core inflation and its components over a full sample period from 2012:Q3 to 2022:Q3, consisting of 42 observations. The mean core inflation rate is 5.7 percent, with a standard deviation of 1.4 percent. The minimum and maximum values of core inflation are 3.6 percent and 9.7 percent, respectively. The components of core inflation are then individually analyzed. Housing has the highest mean inflation rate at 5.6 percent, with a relatively higher standard deviation of 2.2 percent. Transport and Communication follow with a mean inflation rate of 5.0 percent and a larger standard deviation of 3.5 percent. Clothing and Footwear exhibit a mean inflation rate of 6.2 percent, while Health and Education have mean inflation rates of 6.0 percent and 5.8 percent, respectively. Personal Care and Effects, Household Goods and Services, Pan, Tobacco and Intoxicants, and Recreation and Amusement demonstrate lower mean inflation rates ranging from 5.1 percent to 5.9 percent.

Table 5 provides a breakdown of inflation measures during different periods: pre-Covid, IT period, and Covid. Comparing these periods to the overall full sample period discussed previously, some interesting patterns emerge. For core inflation, the mean remains relatively stable across the different periods, ranging from 4.9 percent to 5.7 percent. However, the standard deviation shows some variations, with the lowest during the IT period (0.8 percent) and slightly higher during the Covid period (0.6 percent). Analyzing the components of core inflation, housing inflation appears to have experienced a decline during the Covid period (3.6 percent) compared to both the pre-Covid (6.4 percent) and IT (5.9 percent) periods. On the other hand, transport and communication inflation increased significantly during the Covid period (9.0 percent) compared to the pre-Covid

Table 4: Full Sample (2012:Q3 to 2022:Q3, 42 observations)

	Mean	S.D.	Min	Max	Weight
Core inflation	5.7	1.4	3.6	9.7	
Components of core inflation					
Housing	5.6	2.2	3.1	12.0	21.3
Transport and Communication	5.0	3.5	-1.6	11.6	18.2
Clothing and Footwear	6.2	3.1	1.2	13.1	13.8
Health	6.0	1.4	3.8	8.8	12.5
Education	5.8	2.1	1.7	10.0	9.4
Personal Care and Effects	5.9	3.1	1.6	14.0	8.2
Household Goods and Services	5.5	2.0	1.8	9.9	8.0
Pan, Tobacco and Intoxicants	7.3	2.6	1.8	11.8	5.0
Recreation and Amusement	5.1	1.0	3.4	7.3	3.6

(3.6 percent) and IT (3.4 percent) periods. Other components such as clothing and footwear, health, education, personal care and effects, and recreation and amusement exhibit varying inflation patterns across the different periods.

Table 5: Comparison of Inflation Measures

	Pre-Covid (2012:Q3 to 2019:Q4)		IT period (2016:Q3 to 2019:Q4)		Covid (2020:Q1 to 2022:Q3)	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Core inflation	5.7	1.6	4.9	0.8	5.7	0.6
Components of core inflation						
Housing	6.4	2.2	5.9	1.4	3.6	0.3
Transport and Communication	3.6	2.6	3.4	1.8	9.0	2.3
Clothing and Footwear	6.4	3.2	3.9	1.5	5.8	2.9
Health	6.0	1.4	5.7	1.7	6.0	1.4
Education	6.6	1.5	5.6	1.1	3.3	1.1
Personal Care and Effects	5.2	2.7	4.9	1.5	7.6	3.5
Household Goods and Services	5.8	1.9	4.4	1.0	4.7	2.2
Pan, Tobacco and Intoxicants	7.8	2.0	6.1	1.3	6.0	3.6
Recreation and Amusement	4.9	0.8	4.6	0.8	5.9	1.2

B Unit-root tests

In our analysis, we utilize the Hodrick-Prescott (H-P) filter to extract the cyclical component from high-frequency (HF) indicators.[28] This cyclical component serves as an essential tool for estimating the demand index, which acts as a proxy for the output gap.

The Hodrick-Prescott (H-P) filter extracts the trend component in a time series. Phillips and Jin (2015) show that when the H-P filter is employed to extract deterministic trends, it does not necessarily eliminate stochastic trends or unit roots. Thus, it is essential to test for unit roots in H-P-filtered cycles derived from high-frequency variables.

All HF indicators show strong evidence against having a unit root, implying they are likely to be stationary time series (Table 6).[29] For CPI core, while the ADF test indicate stationarity at the 10% significance level, it does not satisfy the stationarity criteria at the more stringent 5% significance level. However, the PP test suggests stationarity at the 5% significance level.

Table 6: Unit root tests on HF indicators

Variable	ADF Test Statistic	PP Test Statistic
Farm tractor sales	-4.3	-6.6
Petroleum consumption	-4.6	-6.9
Crude steel Production	-4.4	-6.3
SCB Credit	-2.6	-2.7
IIP	-5.0	-5.9
IIP Capital goods	-4.9	-6.6
IIP Consumer durable goods	-5.1	-7.0
IIP Consumer non-durable goods	-5.1	-7.4
IIP Primary goods	-4.4	-5.4
CPI Core	-1.5	-10.0
Domestic passenger growth	-4.6	-7.0
M3 growth rate	-2.0	-12.3

Note: Critical values for ADF and PP tests at the 5% significance level are -1.95 and -2.88, respectively.

[28] We employ the HP filter for its superior turning point signal stability, as suggested by Nilsson and Gyomai (2011), while acknowledging its relatively weaker numerical precision.

[29] We use the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests.

C State space representation

The state-space model used in our analysis can be represented as follows:

$$\mathbf{Y}_t = \mathbf{A}\mathbf{X}_t \tag{8}$$

$$\mathbf{X}_t = \mathbf{B}\mathbf{X}_{t-1} + \mathbf{E}_t \tag{9}$$

In matrix notation, this can be written as:

$$\begin{bmatrix} Y_{1t} \\ Y_{2t} \\ \vdots \\ Y_{Kt} \\ \pi_t^{core} \end{bmatrix}_{(K+1)\times 1} = \begin{bmatrix} \lambda_1 & 0 & 1 & 0 & \dots & 0 & 0 \\ \lambda_2 & 0 & 0 & 1 & \dots & 0 & 0 \\ \vdots & \dots & & & & & \\ \lambda_K & 0 & \dots & 0 & 1 & 0 & 0 \\ \beta_1 & \beta_2 & 0 & \dots & 0 & 1 & 1 \end{bmatrix} * \begin{bmatrix} X_t \\ X_{t-1} \\ \epsilon_1^Y \\ \epsilon_2^Y \\ \vdots \\ \epsilon_K^Y \\ \pi_t^{trend} \\ \epsilon_t^{\pi} \end{bmatrix}_{(K+4)\times 1}$$

$$\begin{bmatrix} X_t \\ X_{t-1} \\ \epsilon_{1t}^Y \\ \epsilon_{2t}^Y \\ \vdots \\ \epsilon_{Kt}^Y \\ \pi_t^{trend} \\ \epsilon_t^{\pi} \end{bmatrix} = \begin{bmatrix} \phi_1 & \phi_2 & 0 & 0 & \dots & 0 & 0 \\ 1 & 0 & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & \rho_1 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & \rho_2 & \dots & 0 & 0 \\ \vdots & \dots & & & & & \\ 0 & 0 & \dots & 0 & \rho_k & 0 & 0 \\ 0 & 0 & \dots & 0 & 0 & 1 & 0 \\ 0 & 0 & \dots & 0 & 0 & 0 & 1 \end{bmatrix} * \begin{bmatrix} X_{t-1} \\ X_{t-2} \\ \epsilon_{1,t-1}^Y \\ \epsilon_{2,t-1}^Y \\ \vdots \\ \epsilon_{K,t-1}^Y \\ \pi_{t-1}^{trend} \\ \epsilon_{t-1}^{\pi} \end{bmatrix} + \begin{bmatrix} \epsilon_t^X \\ 0 \\ e_{1t} \\ e_{2t} \\ \vdots \\ e_{Kt} \\ \zeta_t \\ \nu_t \end{bmatrix}$$

Our goal is to make inference about the states $\mathbf{X}_t$ based on a set of observations $\mathbf{Y}_t$. The *Kalman Filter* is an algorithm for inferring the current state given the history of observations in a state-space model when the parameters are known. The intuition underlying the Kalman filter can be summarized in two steps: First, Time Update, at the beginning of time t, we want to form an optimal predictor of $\mathbf{Y}_t$ based on all the information available up to time $t-1$. Second, Measurement Update, once $\mathbf{Y}_t$ is realized at the end of time t, the prediction error can be calculated as $\psi_{t|t-1} = \mathbf{Y}_t - \mathbf{E}(\mathbf{Y}_t|\mathbf{I}_{t-1})$. The prediction error contains new information about $\mathbf{X}_t$ beyond that contained in $\mathbf{E}(\mathbf{X}_t|\mathbf{I}_{t-1})$. The updated estimate of

$\mathbf{X}_t$, denoted as $\mathbf{E}(\mathbf{X}_t|\mathbf{I}_t)$, is obtained as a weighted average of $\mathbf{E}(\mathbf{X}_t|\mathbf{I}_{t-1})$ and the new information contained in the prediction error $\psi_{t|t-1}$, with the weight assigned to the new information being the Kalman gain.

D Implementation of the EM Algorithm

The Expectation-Maximization (EM) algorithm is employed in this study to obtain the demand index derived from HF indicators. In this section of the appendix, we provide an overview of the implementation of the EM algorithm and highlight some key considerations.

Since the application of Kalman filter requires model parameters to be known, we employ the EM algorithm to estimate the parameters of the state-space model. The EM algorithm iteratively estimates the parameters based on the observed data and the current parameter values. The steps involved are as follows:

1. Start with the initial values of the parameters.

2. E-step: Compute the conditional expectation of the complete data likelihood. This is done by using the Kalman smoothers to obtain the desired conditional expectations given the data and the current parameter values.

3. M-step: Find the optimal estimates and update the parameters.

4. Repeat steps 2 and 3 until convergence.

By employing the EM algorithm, we estimate the parameters of the state-space model and utilize the Kalman filter to make inferences about the unobserved states. The EM algorithm is a hill-climbing algorithm that aims to maximize the likelihood function. However, like all hill-climbing algorithms, it can get stuck on local maxima (Holmes, Ward, and Scheuerell (2021)). To mitigate this issue, a search of the initial conditions space is conducted. A brute force random Monte Carlo search has been found to be effective in exploring a wide range of initial conditions and improving the likelihood of finding the global maximum (Biernacki, Celeux, and Govaert (2003)).

The EM algorithm quickly converges in the vicinity of the maximum likelihood, but the final approach to the maximum can be relatively slow compared to quasi-Newton methods. However, one advantage of the EM algorithm is its robustness to initial conditions choices. It can rapidly approximate the maximum likelihood estimates, particularly in high-dimensional models (Holmes, Ward, and Scheuerell (2021)).

In this study, the R package MARSS (Multivariate Autoregressive State-Space) is utilized for implementing the EM algorithm. The MARSS package provides a comprehensive framework for model estimation and allows for the integration of different optimization techniques. It offers the flexibility to use the BFGS (Broyden-Fletcher-Goldfarb-Shanno) method for refining and polishing the estimates obtained from the EM algorithm.

In summary, the implementation of the EM algorithm in obtaining the demand index involves considerations such as initial conditions exploration, iterative estimation, and potential hybridization with other optimization techniques. The MARSS package in R provides a robust framework for implementing the EM algorithm and fitting MARSS models, offering flexibility and integration with different optimization methods.

E Sensitivity to other high frequency indicators

Table 7 displays the relative RMSE values for n-quarter ahead forecasts from various measures of the EM algorithm based demand index (D10). The forecasts are compared for different quarters (1, 2, 3, and 4 quarters ahead). The values in the table represent how well each forecasting method performs relative to the baseline (ARIMA + D10), with lower values indicating better performance. Different variations of "D10" are considered by substituting some variables (Passenger traffic, SCB Credit, Tractor sales) in the demand index with broad money M3. Table 7 reveals that substituting the variables within the D10 demand index with the "M3" variable generally enhances forecast accuracy. This leads to diminished relative RMSE values, suggesting that liquidity in the economy holds some explanatory capacity in predicting core inflation, when compared to the variables it replaces. However, replacing M3 with IIP worsens the results. Hence, the results are not robust, and depend on the indicator replaced.

Table 7: Relative RMSE of n-quarter ahead forecasts

Aggregate forecasting	1-quarter	2-quarter	3-quarter	4-quarter
Arima + D10	1.000	1.000	1.000	1.000
D10 includes M3 instead of				
Passenger traffic	0.856	0.883	0.892	0.971
Tractor sales	0.858	0.907	0.909	0.955
SCB Credit	0.854	0.909	0.913	0.963
IIP	1.110	1.268	1.497	1.565

F Bayesian Approach: MCMC Algorithm

The Markov Chain Monte Carlo (MCMC) algorithm is employed in this study to obtain the demand index derived from HF indicators. In this section of the appendix, we provide an overview of the implementation of the MCMC algorithm and highlight some key considerations.

In the Bayesian approach, the main idea is to determine the posterior distribution of all unknown parameters conditional on the latent factor and then determine the conditional distribution of the latent factor given the observables and the other parameters (Sharma and Padhi (2020)). Moreover, the Markov Chain Monte Carlo method is used to sample the joint posterior distribution of the unobserved factors and unknown parameters on the full set of conditional parameters. The Markov chain samples sequentially from the conditional distributions for parameters/factors and factors/parameters and at each stage, use the previous iterations drawing as the conditioning variables, ultimately yielding drawings for the joint posterior distribution of (parameters, factors). The prior distribution of the parameters is selected in such a way that the posterior distribution of parameters is determined by observable data rather than its prior.

In this approach, the JAGS program with R is utilized to implement the Bayesian modeling (Plummer, Stukalov, and Denwood (2023)). JAGS stands for Just Another Gibbs Sampler. It is a program for the analysis of Bayesian hierarchical models using Markov Chain Monte Carlo simulation. It uses a dialect of the BUGS language, similar to but a little different from OpenBUGS and WinBUGS.

G Forecasting performance

G.1 Absolute RMSE for 4-quarter ahead forecasts

Table 8 presents the root mean square error (RMSE) of n-quarter ahead forecasts using various model specifications. In the context of aggregate forecasting, the ARIMA model performs reasonably well across all forecast horizons. Adding exogenous variables such as D10, BD10, HP gap, and SS improves the accuracy of the forecasts to some extent. When combining dis-aggregate forecasts, using a common model for all components yields mixed results. However, employing distinct models for transport and communication (T & C) component leads to better accuracy, particularly when including additional factors like REER, fuel, and oil (prices). Overall, the combination of ARIMA, D10, SS, and oil (prices) consistently delivers improved forecast accuracy for both aggregate and dis-aggregate scenarios.

Table 8: RMSE of n-quarter ahead forecasts

A. Aggregate forecasting	**1-quarter**	**2-quarter**	**3-quarter**	**4-quarter**
ARIMA	0.254	0.434	0.577	0.648
ARIMA + D10	0.239	0.406	0.439	0.324
ARIMA + BD10	0.289	0.537	0.692	0.658
ARIMA + HP gap	0.259	0.480	0.597	0.597
ARIMA + SS	0.239	0.539	0.791	0.797
ARIMA + D10 +SS	0.262	0.513	0.654	0.715
ARIMA + BD10 + SS	0.285	0.564	0.720	0.720
B. Combination of dis-aggregate forecasts				
B1. Common model for all components				
ARIMA	0.351	0.696	0.910	1.085
ARIMA + D10	0.309	0.603	0.757	0.804
ARIMA + BD10	0.314	0.701	0.956	1.109
ARIMA + HP gap	0.295	0.505	0.682	0.776
ARIMA + SS	0.255	0.565	0.770	0.873
ARIMA + D10 + SS	0.251	0.531	0.690	0.761
ARIMA + BD10 + SS	0.210	0.518	0.779	0.882
ARIMA + D10 + SS + Oil	0.267	0.629	0.850	0.955
ARIMA + BD10 + SS + Oil	0.232	0.543	0.755	0.806
B2. Distinct model for T & C, but common for others				

B2.1 ARIMA + D10 + SS + REER + Fuel				
T & C» D10 + SS + REER + Oil	0.157	0.431	0.713	0.796
T & C» D10 + REER + Oil	0.229	0.460	0.658	0.700
T & C» D10 + Oil	0.229	0.497	0.714	0.804
T & C» REER + Oil	0.206	0.526	0.906	1.027
B2.2 ARIMA + D10 + SS + Fuel				
T & C» D10 + Oil	0.237	0.464	0.554	0.580
T & C» SS + Oil	0.207	0.492	0.695	0.762
T & C» D10 + SS + Oil	0.225	0.466	0.620	0.710
B2.3 ARIMA + D10 + SS				
T & C» Oil	0.260	0.516	0.645	0.686
T & C» D10 + Oil	0.261	0.511	0.610	0.655
T & C» SS + Oil	0.229	0.527	0.719	0.773
T & C» D10 + SS + Oil	0.243	0.493	0.628	0.696

G.2 Relative RMSE for 8-quarter Ahead Forecasts

Table 9 provides insights into the performance of various forecasting models based on the relative root mean squared error (RMSE) of n-quarter ahead forecasts. Panel A focuses on aggregate forecasting. Combining different variables with the ARIMA model produces varying results. The inclusion of D10 and SS improves forecast accuracy compared to the baseline ARIMA model across multiple horizons. Similarly, adding BD10 and SS leads to further reductions in RMSE. However, relying solely on SS shows diminishing performance beyond the 4-quarter horizon.

Panel B examines dis-aggregate forecasting using two approaches. Under Panel B1, where a common model is used for all components, incorporating variables like D10, BD10, and SS enhances forecast accuracy for most horizons. Notably, the inclusion of SS consistently reduces RMSE across all horizons. In Panel B2, where distinct models are used for "Transport and Communication" (T & C), the results vary based on the combination of variables. Models incorporating D10, SS, REER, and Fuel (prices) demonstrate lower RMSE values, indicating their effectiveness in capturing the forecasting dynamics for T & C. Notably, the inclusion of Oil as a variable generally improves forecast accuracy. These findings emphasize the significance of selecting appropriate variables and models for different forecasting scenarios. The impact of these choices on forecast accuracy varies depending on the context and forecast horizon.

Table 9: Relative RMSE of n-quarter ahead forecasts

A. Aggregate forecasting								
Model	1-quarter	2-quarter	3-quarter	4-quarter	5-quarter	6-quarter	7-quarter	8-quarter
ARIMA	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
ARIMA + D10	1.103	1.119	0.973	0.544	0.511	0.481	0.441	0.618
ARIMA + BD10	1.115	1.243	1.279	0.998	1.111	0.967	0.950	0.823
ARIMA + HP gap	1.077	1.033	1.089	0.968	1.023	1.139	1.031	1.077
ARIMA + SS	1.070	1.462	2.118	2.120	1.925	1.906	1.504	1.499
ARIMA + D10 + SS	1.230	1.451	1.774	1.959	1.726	1.572	1.221	1.102
ARIMA + BD10 + SS	1.027	1.259	1.596	1.499	1.373	1.247	0.990	0.811
B. Combination of dis-aggregate forecasts								
B1. Common model for all components								
Model	1-quarter	2-quarter	3-quarter	4-quarter	5-quarter	6-quarter	7-quarter	8-quarter
ARIMA	1.274	1.481	1.934	2.296	2.258	2.309	2.089	2.043
ARIMA + D10	1.229	1.395	1.605	1.712	1.650	1.619	1.467	1.458
ARIMA + BD10	1.041	1.482	1.974	2.313	2.265	2.183	2.062	1.891
ARIMA + HP gap	1.101	1.048	1.439	1.673	1.739	1.811	1.651	1.541
ARIMA + SS	0.770	1.074	1.648	1.732	1.785	1.735	1.546	1.325

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Table 9 – continued from previous page

Model	1-quarter	2-quarter	3-quarter	4-quarter	5-quarter	6-quarter	7-quarter	8-quarter
ARIMA + D10 + SS	0.715	0.936	1.359	1.333	1.337	1.246	1.084	0.833
ARIMA + BD10 + SS	0.578	1.005	1.563	1.617	1.676	1.603	1.436	1.200
ARIMA + D10 + SS + Oil	0.948	1.530	2.037	2.126	1.989	1.804	1.524	1.424
ARIMA + BD10 + SS + Oil	1.004	1.464	1.923	2.012	1.982	1.850	1.657	1.520
B2. Distinct model for T & C								
Model	1-quarter	2-quarter	3-quarter	4-quarter	5-quarter	6-quarter	7-quarter	8-quarter
ARIMA + D10 + SS + REER + Fuel								
T & C » D10 + SS + REER + Oil	0.707	1.146	1.733	1.808	1.828	1.716	1.522	1.278
T & C » D10 + REER + Oil	0.850	1.232	1.666	1.704	1.769	1.628	1.508	1.269
T & C » D10 + Oil	1.033	1.248	1.503	1.484	1.547	1.406	1.339	1.148
T & C » REER + Oil	0.771	1.218	1.801	2.085	2.143	2.037	1.907	1.627
ARIMA + D10 + SS + Fuel								
T & C » D10 + Oil	1.141	1.239	1.304	1.211	1.233	1.079	1.062	0.932
T & C » SS + Oil	0.739	0.997	1.333	1.323	1.438	1.324	1.254	0.994
T & C » D10 + SS + Oil	0.879	1.081	1.398	1.314	1.323	1.202	1.049	0.868
ARIMA + D10 + SS								
T & C » Oil	0.948	1.222	1.504	1.533	1.584	1.451	1.398	1.177
T & C » D10 + Oil	1.108	1.352	1.547	1.428	1.394	1.212	1.126	0.989

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Table 9 – continued from previous page

Model	1-quarter	2-quarter	3-quarter	4-quarter	5-quarter	6-quarter	7-quarter	8-quarter
T & C » SS + Oil	0.759	1.193	1.660	1.668	1.676	1.536	1.387	1.139
T & C » D10 + SS + Oil	0.946	1.320	1.791	1.799	1.683	1.538	1.299	1.132

Note: This table provides relative RMSE values, with the RMSE from the ARIMA model in the aggregate forecasting framework serving as the baseline. It is important to note that the baseline value varies for each forecast horizon, enabling a meaningful comparison between different models within a specific forecast horizon.

H Staggered Availability of Data

Table 10 presents various economic indicators, their release timing, and the extent of information available for analysis. When there is minimal information, the analysis is centered around forecasts made at the outset of each quarter. Within this context, the table employs a visual representation wherein tick marks (✓) denote the extent of available data. Specifically, the tick marks are indicative of the number of months of data that is at hand for the corresponding high-frequency indicator from the previous quarter. For instance, consider the case where forecasting takes place in early January. During this period, the Industrial Production Index data for the quarter spanning October to December is still incomplete. As of this point, only data for the month of October has been made available. In the minimal information column, the presence of a single tick mark denotes the availability of data for just one month. The same logic and interpretation can be extrapolated to the partial information case as well.

Table 10: Release Timing and Information Availability of Economic Indicators

Indicator	**Release Timing**	**Minimal Information**	**Partial Information**
Automobile Sales: Domestic Passenger Vehicle	2nd week of next month	✓✓	✓✓✓
Automobile Sales: Domestic Two Wheelers	2nd week of next month	✓✓	✓✓✓
Automobile Sales: SIAM: Domestic: Total	2nd week of next month	✓✓	✓✓✓
Farm Tractor Sales (Including Exports)	2nd week of next month	✓✓	✓✓✓
Petroleum Consumption	3rd week of next month	✓✓	✓✓✓
Crude Steel Production	2nd-3rd week of next month	✓✓	✓✓✓
Non-Oil Imports	15-16th of next week	✓✓	✓✓✓
Non-Oil Exports	15-16th of next week	✓✓	✓✓✓
SCB: Non Food Credit	1 and half month delay	✓	✓✓
Industrial Production Index (all components)	on 12th of every month with time lag of 42 days	✓	✓✓
Cement Production		✓✓	✓✓✓
Core CPI	3rd week of next month	✓✓	✓✓✓
Domestic Passenger Traffic	1st week of next month	✓✓	✓✓✓

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