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# Real-Time Monitoring of the Indian Economy – An Alternative Approach

**By**

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*With more frequent and up to date dataflow, the daily/weekly indicators allow model-based monitoring of economic activity to be more real time, thus enhancing their relevance for policy making. Anomaly in the general trend of the indicators have driven existing models to go off the mark with exorbitantly high error component post the pandemic. In this paper, we extend our existing nowcasting model for quarterly GDP in India which is based on monthly indicators to include additional data in the form of daily/weekly indicators. We develop a factor augmented MIDAS model by integrating two composite indices – at monthly and weekly frequency, respectively, constructed using the dynamic factor model for the purpose of nowcasting quarterly GDP. This framework allows to leverage detailed and comprehensive coverage of economic activity through monthly indicators while also updating nowcasts more frequently based on latest information content embedded in the weekly indicators. The results show that the FA-MIDAS produces a lower out of sample forecast error compared with univariate ARIMA and standalone monthly indictor based DFM nowcasting models during the post-pandemic period.*

## I. Introduction

The cataclysmic consequences of COVID pandemic on economic activity have posed fresh challenges to the economic forecasting. The size of the fluctuations has been unprecedented, with highest ever year-on-year contraction in gross domestic product (GDP) in Q1:2020-21 at (-) 23.4 per cent which subsequently eased to (-) 5.7 per cent in Q2:2020-21. Such a huge anomaly in the general trend of the indicators has driven existing models to go off the mark with exorbitantly high error component. In the presence of largescale fluctuations in the economy aggravated by the multiple economic shocks that followed the COVID-19 pandemic, the challenge for the forecasters has been to generate forecasts in the absence of adequate data. The

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nowcasting literature post pandemic mainly highlights two ways to address this challenge – subjective judgement or prior knowledge that could be drawn from economic theory, or resort to external/unconventional sources of data. For instance, epidemiological data, mobility data, air quality data were of special interest for forecasters and policy makers during the pandemic. Driven by the above motivation, the paper attempts to adapt and upscale the existing nowcasting models by expanding their information set to include weekly variables, in order to better reflect the atypical changes and fluctuations which the economy has been undergoing since the outbreak of the pandemic.

In India, the GDP estimates, released on a quarterly[2] and annual basis by the National Statistics Office (NSO), have been considered as the official indicator of real economic activity. However, release of quarterly GDP estimates usually involves a lag of sixty days from the end of the reference quarter. With regard to monetary policy of the central banks (which follows a bi-monthly cycle in case of India), given its forward looking nature, rely heavily on early estimates of GDP for the current quarter as well as reliable forecasts for the subsequent quarters. Nowcasting which concerns predicting the present, the very near future and the very recent past serve as a very useful tool to produce near term projection of GDP and has been used extensively by Central banks across the world.

Nowcasting exercise has significantly evolved overtime from qualitative judgement and small-scale models like bridge equations, for example, Trehan (1989) or Parigi and Schlitzer (1995), Rünstler, & Sédillot (2003), Kitchen and Monaco (2003), Parigi and Golinelli (2007), and Diron (2008), Bhattacharya *et al.* (2011)) into more sophisticated and complicated modelling. Within the single equation framework, advanced models involving mixed frequency data sampling (MIDAS) have been developed which proposed solution to forecasting low frequency variable with high frequency predictors without frequency conversion as it involves a parsimoniously parameterized distributed lag polynomial for the high frequency regressors (Ghysels, Santa-Clara, and Valkanov (2004); Clements and Galvo (2008) and Marcellino and

[2] The idea of quarterly estimates initially came from the International Monetary Fund (IMF), works to achieve sustainable growth and prosperity for all of its 190 member countries, because they wanted to track the economies on a more frequent basis than annually. With the SDDS it became a part and parcel of economic monitoring.

Schumacher (2008). In MIDAS models, parameters depend on forecast horizon and on the pattern of data availability, and in case of parameters instability, they can be also more robust compared to a system solution. However, the most popular and widely used nowcasting models which are also considered as seminal contributions in nowcasting literature in recent times involve system solution as they provide an improved framework to generate projections for multiple variables and allows to compute model-based surprise in each data release which in turn result in nowcast revision. Seminal works in this framework, notably, Evans (2005); Giannone, Reichlin and Small (2008); Banbura and Modugno (2014) used dynamic factor model (DFM) which is particularly useful to efficiently handle a large set of high frequency indicators. to avoid the curse of dimensionality while effectively capturing the salient features of each data. A 25-indicator dynamic factor based nowcasting model for Indian GDP developed by the authors showed significantly improved nowcast performance over benchmark ARIMA model and naïve model in the pre-pandemic period (Prakash *et.al*, 2021). However, one common aspect in all alternative nowcasting models of GDP is that they use indicators at monthly frequency for projecting quarterly GDP.

At the onset of the COVID pandemic, majority of the conventional economic indicators available at monthly frequency, which are released with a lag, were found to be inadequate in depicting the most recent happenings. Traditional hard indicators such as, automobile sales, bank credit, industrial production *etc.*, are released with a lag of about thirty to forty-five days. Therefore, the period since the outbreak of the pandemic which demanded prompt policy actions to safeguard the economy and livelihood, saw greater use of high frequency indicators (HFIs). As the global economy continues to recover from the pandemic, multiple shocks such as Russia-Ukraine war triggering commodity price spike, supply chain disruption and more recently failure of Silicon Valley Bank (SVB) and Signature Bank in the US, and bailout of Credit Suisse, continue to rattle the global economy. This has accentuated the need for real time assessment of the economy for effective policy making. It was found that with technological advancement and growing digitalisation, newly available daily/weekly data pertaining to various segments of the economy made available by the ministries, regulatory bodies and other agencies emerged as useful sources of information to wedge the time lag and present the most updated status of economic activities.

Daily/weekly indicators also contribute to expand and compliment the information set for the bi-monthly monetary policy in India. The information set during each round of policy varies due to asynchrony in the frequency of the macroeconomic indicators, *viz.* the data for GDP is released quarterly; and conventional high frequency indicators (HFIs) are available at most at monthly frequency and their release calendar (Table 1). This information gap can be bridged by the weekly/daily indicators by making available information till a week prior to the monetary policy deliberations.

**Table 1: Information Availability for Monetary Policy**

| Round | Reference Quarter | Availability of Major Indicators | | | | Weekly Index (complete up to) |
|---|---|---|---|---|---|---|
| | | GDP | Monthly HFIs | | | |
| | | | Complete | Partial | Scant | |
| April (t) | Q1 (t) | Q3 (t-1) | January | February | March | March |
| June (t) | Q1 (t) | Q4 (t-1) | - | April | May | May |
| August (t) | Q2 (t) | Q4 (t-1) | April, May | June | July | July |
| October (t) | Q3 (t) | Q1 (t) | July | August | September | September |
| December (t) | Q3 (t) | Q2 (t) | - | October | November | November |
| February (t) | Q4 (t) | Q2 (t) | October, November | December | January | January |

**Note**: 1. t indicates the current fiscal year.
2. Author's compilation.

In view of the above, the authors had published a research article titled 'Real-Time Monitoring of the Indian Economy' in the RBI Bulletin in August 2022[3], To draw out the maximum information from the weekly indicators, a suite of different models or indices have been developed to monitor the economic activities. Three alternative indices at weekly frequency have been developed, all serving distinct purposes such as, tracking developments in the real economy on year over year basis, relative to pre-pandemic levels and reflecting sequential dynamics as well. Extending the existing work, in this paper, authors have attempted to improvise the timely tracking of economic activities by combining the monthly dynamic factor model and the weekly activity index in a

[3] Authors have also presented the work in the Indian Association for Research in National Income and Wealth (IARNIW) Seminar on National Accounts in November 2022 and the comments received in the seminar have been incorporated in the current version.

factor-augmented MIDAS (FA-MIDAS) framework. This framework allows to leverage detailed and comprehensive coverage of economic activity through monthly indicators while also updating nowcasts more frequently based on latest information content embedded in the weekly indicators. The results show that the FA-MIDAS produces a lower out of sample forecast error compared with univariate ARIMA and standalone monthly indictor based DFM nowcasting models during the post pandemic period.

The rest of the article is structured as follows – Section II presents a review of recent literature on GDP nowcasting. Section III and IV discuss the econometric framework of the models employed, and data used in the models respectively. Section V presents real time tracking activity through weekly indices and nowcasting results. Section VI concludes highlighting on existing limitations and future scopes.

## II. Literature Review

The earliest instance of monitoring the economic activities or business cycles with the help of economic indicators dates to the 1930s when National Bureau of Economic Research, as a part of its research programme, used coincident and leading indicators for the US economy (Burns and Mitchell, 1938). Though the idea behind the factors capturing the features of the business cycles was forwarded by Sargent and Sims (1977), Stock and Watson (1989) in a more mathematical manner used the multivariate content for predicting the business cycles and specified a single index dynamic factor model (DFM) for the coincident variables. With significant refinements in the factor models over the period, the indicator based nowcasting approach particularly gained reverence in the central banking arena with the seminal work by Giannone *et al.* (2008). Since then, incorporating the further improvements (Giannone *et al.* 2013), many central banks and international organisation have regularly come up with updated and customised models for nowcasting the GDP.

The temporary halt during the pandemic year though provided an aberration in the regular release of many conventional indicators, it on the flipside provided a thrust in the release of new indicators at even higher frequency *i.e.*, on a weekly, and daily basis. These new HFIs, led to the proliferation of GDP nowcasting exercises across central banks in a timely manner using the weekly indicators (Table 2).

| Table 2: Weekly tracking - International Experience | | | |
|---|---|---|---|
| **Central Bank/ Agency** | **Index Description** | **Methodology** | **Activity Tracking** |
| Federal Reserve Bank of New York | Weekly Economic Index comprising a set of 10 HFIs | Principal Component Analysis (PCA), DFM | Gives weekly picture of the real economic activity based on the latest available dataset at a fixed vintage, used to nowcast quarterly GDP |
| IMF | Weekly and monthly indicators of the respective economies are aggregated to quarterly frequency to nowcast the GDP | DFM and Machine learning | Nowcasting GDP of European Economies |
| OECD | Provides an estimate of weekly GDP based on the Google Trends search data and machine learning | Machine learning | Two trackers estimating – i. Weekly GDP relative to the same week in the previous year. ii. GDP level Tracker provides estimates of the level of weekly GDP relative to 2019 Q4 |
| Banca D' Italia | Italian Weekly Economic Index (ITWEI) constructed based on 12 daily/weekly indicators | PCA | Single factor constructed using PCA which is then normalised to match the mean and standard deviation of the Italian GDP |
| Deutsche Bundesbank | Mixed frequency dataset comprising readily available weekly HFIs along with the monthly industrial output and latest GDP estimate | PCA | Rolling 13-week growth rate index and at the quarter-end, the values of the index can be interpreted approximately as quarter-on-quarter rate of change. |

**Sources:** Federal Reserve Bank of New York; IMF; OECD; Banca D' Italia; and Deutsche Bundesbank.

One of the early attempts of tracking the rapid economic developments was initiated in the US. The Federal Reserve Bank of New York developed a weekly economic index (WEI) comprising 10 high frequency indicators (Lewis *et al.,* 2020)[4]. Applying machine learning techniques to a panel of google trends data, OECD also provides a real time high frequency indicator of economic activity for 46 countries (including India). The algorithm extracts and compiles information for a number of variables based on google search categories and collection of related keywords, and groups them under separate heads. It provides a weekly estimate of the GDP relative to the

[4] Publication of the Nowcast however has been suspended since September 3, 2021, as the uncertainty around the pandemic and the consequent volatility in the data posed a number of challenges to the Nowcast model.

same week of the previous year, since early 2020 to the latest week with a 95 per cent confidence interval bands. Banca D' Italia on January 2020 also attempted to exploit the information content of the high frequency (weekly and daily) variables to construct a timely indicator to monitor the GDP growth rate on a weekly basis (Delle Monache *et al.* 2021). An unconventional weekly economic activity index for Germany created by the Deutsche Bundesbank, Germany which uses the high frequency variables track the quarterly GDP appropriately (Eraslan and Gotz, 2020). It used a mixed frequency dataset comprising of the quickly available high frequency variables along with the monthly industrial output and latest GDP estimate.

Given the evolving nature of India's data infrastructure, the process of nowcasting India's GDP has also matured over the time with new and high frequency indicators being made available particularly with the outbreak of the pandemic. Bhattacharya et al. (2011) combines univariate quarterly models with bridge models that exploit the available monthly indicators containing information on current quarter developments. Bridge models are found to perform satisfactorily in predicting current quarter GDP growth. The analysis also suggests mixed evidence about the additional predictive power of Indian survey data with respect to the hard data already used in the national accounts.

Using single-index dynamic factors, Bhadury *et al.* (2018) nowcast quarterly GDP growth with a sequentially expanding list of 6, 9 and 12 high-frequency indicators. The exercise has been performed in two stages. In the first stage, factor has been estimated based on chosen indicators which is then used to augment a parsimonious auto-regressive (AR) model with contemporaneous information to obtain nowcast of the current quarter GDP. Few studies have focused on sector-specific nowcasting as well. Nowcasting the sales growth of real estate companies using Google search data is one such example in big data analytics (Mitra *et al.*, 2017). The article concludes that the search intensity information improves precision relative to other benchmark approaches while nowcasting the current quarter sales. Another paper by Bhadury et al. (2018) also use evening-hour luminosity as a crucial high-frequency indicator to nowcast non-agriculture GVA. Changes in nightlight intensity contain information about economic activity, especially in countries with a large informal sector and significant data challenges, including in India. As per the findings, there has been significant improvement in nowcast of 'trade, hotels, transport, communication and services related to broadcasting' bloc of the Indian GVA with the addition of evening-hour luminosity.

In the context of COVID-19 recovery, an Economic Activity Index for India using 27 monthly indicators constructed using a DFM provides a tool for activity tracking (Bhadury et al., 2020). The study also estimates activity index separately for the industrial sector, services sector and global factors and observed that the industrial sector is faster to recuperate than the contact-intensive service sectors on the path to normalisation. Using only the payment indicators, Kumar et al. (2022) also attempted to forecast the India's GVA through a hybrid machine learning approach using MIDAS in combination with Support Vector Machine (SVM). Substantial increase in predictive accuracy for the nowcasts generated by the hybrid approach and the RMSFE weighting strategy has been demonstrated in their exercise.

With increasing global related risks, the spillovers of the global activity has also made it imperative for the central banks to consider nowcasting global GDP growth. Bank of England nowcasts UK exports-weighted as well as total output-weighted aggregate of world GDP growth. However, the performance of the nowcasting models do not remain constant over time, and periodic improvements in the model specifications become essential for minimising the forecasting errors (Feldkircher et al., 2015). Gupta *et al.,* (2022) also estimated a nowcast of the global growth on an annual basis using the data on trade, industrial production and purchasing manager's index.

Weekly monitoring of the Indian economy was also synchronous to the international experience which assumed greater importance during the pandemic due to disruptions or delay in the release of conventional monthly indicators, the policymakers and private stakeholders resorted to daily/weekly indicators to monitor the economy. Unlike other central banks or statistical agencies, although no official weekly nowcast of the GDP was published in India, several indicators developed by the research teams of private stakeholders were widely discussed among the policy makers. It includes the Nomura India Business Redemption Index (NIBRI), Narrow Recovery Index by Citi bank, Business Activity Index, State Bank of India *etc*. Normalising to February 2020 level (considered as 100), the NIBRI is calculated using Google's daily community data on mobility around the workplace and retail and recreation spots, Apple Map's index for driving mobility, weekly surveys on labour participation rate, and seasonally adjusted trends in weekly electricity demand. Owing to the country wide lockdown induced restrictions, it was found that the activity dropped around 56 percentage points (pp) to a low of 44.4 by end-April 2020.

## III. Econometric Framework

FA-MIDAS framework used in this paper involves two stages of estimation. First stage involves generating a composite monthly index from a large set of monthly indicators in a single-factor dynamic factor model. Similarly, a composite index at weekly frequency based on a set of weekly indicators (and daily indicators aggregated to weekly frequency) has also been constructed. In the next stage, both the monthly and the weekly factors are integrated into a MIDAS framework with quarterly GDP growth as the low frequency dependent variable and both the monthly and the weekly indices as the high frequency predictors.

*Dynamic Factor Model*

The leading framework for the construction of a composite index from multiple time series is the dynamic factor model as developed by Geweke (1970) and Sargent and Sims (1977). Factor model allows using a rich dataset with inclusion of large set of input variables alongside dealing with the curse of dimensionality by capturing the movements of the macroeconomic variables in relatively few factors. The essence of dynamic factor model is to produce a small number of unobserved or latent series which encapsulate the co-movements of the observed series of the constituent indicators. Mathematically, the dynamic factor model posits the observed series as the sum of a vector of the common factors and the vector of idiosyncratic disturbances.

$$x^M_t = \mu + \Lambda^M F_t + \epsilon^M_t \qquad (1)$$

The vector of stationary monthly frequency input variables is denoted as $x^M_t = (x_1{}^M_t, x_2{}^M_t, \ldots\ldots, x_n{}^M_t)$ which also contains missing observations. Appropriate transformations are applied to the monthly series as discussed in the above section. Input variables $x^M_t$ are assumed to have the following factor structure representation:

Where $F_t$ is an r × 1 vector of unobserved factors of monthly frequency, $\Lambda^M$ denotes the factor loadings for the monthly variables and $\epsilon_t$ is a vector of idiosyncratic error components which follow the AR(1) process $\epsilon^M_{i,t} = \alpha i\ \epsilon^M_{i,t-1} + e_{i,t}$ where $e_{i,t} \sim$ i.i.d. N(0,

$\sigma^2_i$) and $E[e_{i,t}, e_{j,ts}] = 0$ for $i \neq j$. The factors are allowed to follow a VAR process of order p:

$$F_t = A_1F_{t-1} + \dots + A_pF_{t-p} + v_t, \qquad v_t \sim \text{i.i.d } N(0,Q) \qquad (2)$$

where the $v_t$ are common shocks and $A_1, \dots, A_p$ are r × r matrices of VAR coefficients. In the presence of a jagged edged data set, this dynamic relationship among the factors provides an edge over a static factor model by adding to the cross-sectional information and increasing the precision of the recent period estimates for which relatively scarce information is available. We have followed the methodology used in Giannone, Reichlin and Small (2008) which uses the Expectation-maximising (EM) algorithm under the state space framework where the unobserved factor is estimated by the Kalman filter. Both our monthly and weekly composite indices are derived using this method.

*Factor Augmented MIDAS*

The expectation maximisation algorithm is well equipped in handling many issues such as a large number of indicators, missing observations, mixed frequency *etc.,* making it the most preferred technique by the forecasters. Although the first stage in our current exercise involves estimation using the EM algorithm, we have adopted MIDAS regression for the second stage for two reasons. The dynamic factor based nowcasting models are designed for nowcasting quarterly GDP using monthly indicators. Therefore, specification of weekly variables would be complicated in a DFM set up. On the other hand, MIDAS is explicitly designed to incorporate variables at mixed frequency and, therefore, allows easier model specifications involving quarterly, monthly, and weekly variables. MIDAS regressions are typically based on distributed lag polynomials and are typically estimated by non-linear least squares (NLS). The contribution of this study has been particularly in augmenting the monthly DFM with an additional factor constructed using the weekly indicators through MIDAS regression, thus leveraging the strengths underlying both the dynamic factor and the MIDAS frameworks. Two factors are created comprising the high frequency information – one based on the monthly indicators and the other based on the weekly indicators to be included in the regression model apart from the lagged value of the quarterly GDP.

Suppose $y_t$ is observed quarterly and we want to explain its variation with the variable $x_i$, which is observed monthly. Since each quarter has three months, the frequency $m$ is 3 in this example. Suppose we assume that the monthly data in the current and the previous quarter has explanatory power. This means that for each quarter $t$ we want to model $y_t$ as a linear combination of variables $x_{3t}$, $x_{3t-1}$, $x_{3t-2}$ observed in the quarter $t$ and variables $y_{t-1}$ and $x_{3(t-1)}$, $x_{3(t-1)-1}$, $x_{3(t-1)-2}$ observed in the previous quarter $t-1$. In matrix notation the MIDAS model (1) for this example is:

$$\begin{bmatrix} y_2 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_{n-1} \end{bmatrix} \alpha_1 + \begin{bmatrix} x_6 & \dots & x_1 \\ \vdots & \vdots & \vdots \\ x_{3n} & \dots & x_{3n-5} \end{bmatrix} \begin{bmatrix} \beta_0 \\ \vdots \\ \beta_5 \end{bmatrix} + \begin{bmatrix} \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

By writing the model in matrix notation we transform the high-frequency variable $x_\tau$ into a low-frequency vector ($x_{3t}, \ldots, x_{3t-5}$). We call this transformation the frequency alignment. Note that we require that the number of observations of $x_\tau$ is exactly 3n.

### *Nowcasting GDP using Weekly Indicators*

We have also performed nowcasting of quarterly GDP using only the weekly variables which was particularly useful during the pandemic period requiring more frequent updates on economic activity. After estimating the WAI based on the constituent series, we rescale the WAI with interpretable unit of quarterly real GDP growth. The choice of y-o-y GDP growth is natural since it is the most widely used macroeconomic indicator of economic activity and aligns with the 52-weeks percentage change used for weekly seasonal adjustment. The scale and shift parameters are estimated using the following regression.

$$GDP^q\ growth = \alpha + \beta WAI^q\ growth + \varepsilon^q \qquad (3)$$

Where, $GDP^q\ growth$ is y-o-y growth in real GDP

$WAI^q\ growth$ is quarterly average of the 52-weeks growth rate in WAI and,

$\varepsilon^q$ is the disturbance term with usual properties.

Thus, the predicted y-variable from equation (3) based on the estimated coefficients $\hat{\alpha}$ and $\hat{\beta}$ provide us the rescaled WAI which is comparable to the quarterly GDP growth. The 13-week moving average of the scaled WAI then used as an indicator for tracking quarterly GDP and the 13-week MA of WAI at the last week of a quarter would precisely represent the average of that quarter.

Apart from their use as inputs for quarterly GDP nowcasting, weekly indicators are also used to construct a diffusion index which tracks momentum (or the week over week changes) in economy activity. The sequential movement in activity on weekly basis has been presented in terms of a diffusion index which uses information from various indicators to present an aggregate picture on whether they are trending upwards or downwards. A diffusion index, however, does not capture the magnitude of the movement. A 15-indicator WDI is constructed following the methodology of the Conference Board[5] shows the co-movement of multiple time series by measuring the proportion of the components that contribute positively to the index. The WDI ranges between 0 and 100 and measures the proportion of the selected variables that contribute positively to the index. For example, an index value 65 is interpreted in the way that 65 per cent of the indicators register week over weak (w-o-w) acceleration while index value of 50 implies w-o-w acceleration in 50 per cent of the indicators in the total set. The methodology for construction the WDI is presented in detailed in Prakash *et al*., (2022).

## IV. **Data**

We have started with the daily or weekly indicators currently available in India from various segments of economic activity. A total of 15 indicators are considered which are broadly categorised into five buckets viz. soft, labour market, demand/sales, mobility, and payments (Table 3).

Since many out of the listed 17 indicators were released for the first time during or post pandemic, getting a long-time series of the listed variables was not possible to have year on year comparison. Accordingly, the indicators considered for our weekly indices are a smaller subset of the list of indicators presented in Table 2.

The soft indicators *viz.* google trends data and the CMIE sentiment indices (consumer sentiments, current economic conditions, and consumer expectations) both of which are available since 2017 (Chart 1 and 2). Both the indices showed a clear dip during

[5] https://conference-board.org/data/bci/index.cfm?id=2180

the time of first lockdown, particularly the sentiment indices took a huge hit by around 60 index points. Recovery in the sentiments which also saw a blip during the more severe second wave of the pandemic, although on a gradual upward trajectory is still far from the pre-pandemic level.

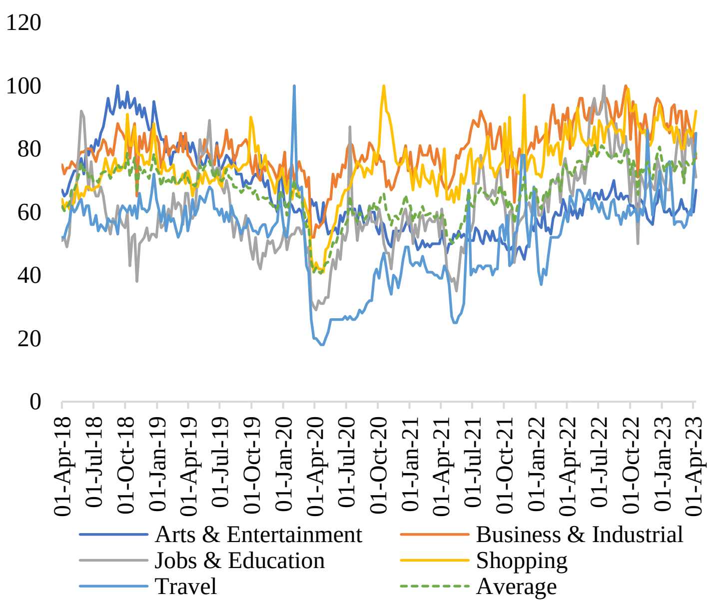
**Table 3: High Frequency Indicators**

| S. No. | Indicators | Frequency | Category | Source |
|---|---|---|---|---|
| 1 | Google Trends | Daily | Soft | Google |
| 2 | Consumer Sentiment Index | Weekly | | CMIE |
| 3 | Consumer Expectation Index | Weekly | | |
| 4 | Current Economic Conditions Index | Weekly | | |
| 5 | Unemployment Rate (%) | Weekly | Labour | |
| 6 | Labour Participation Rate (%) | Weekly | | |
| 7 | Electricity Generation | Daily | Demand/Sales | Power System Operation Corporation Limited (POSOCO) |
| 8 | Motor Vehicle Registration | Weekly | | Vahan, Ministry of Road Transport and highways |
| 9 | Railway Freight Loading | Daily | | Ministry of Railways |
| 10 | Air Cargo Traffic | Daily | | Airport Authority of India (AAI) |
| 11 | Railway Passengers | Daily | Mobility | Ministry of Railways |
| 12 | Mobility (Retail, Grocery, Park, Transit & Workplace) | Daily | | Google |
| 13 | Aircraft Traffic | Daily | | AAI |
| 14 | Airport Footfall | Daily | | AAI |
| 15 | RTGS | Daily | Payments | RBI |
| 16 | Retail Payments | Daily | | |
| 17 | ATM and AePS Withdrawal | Daily | | |

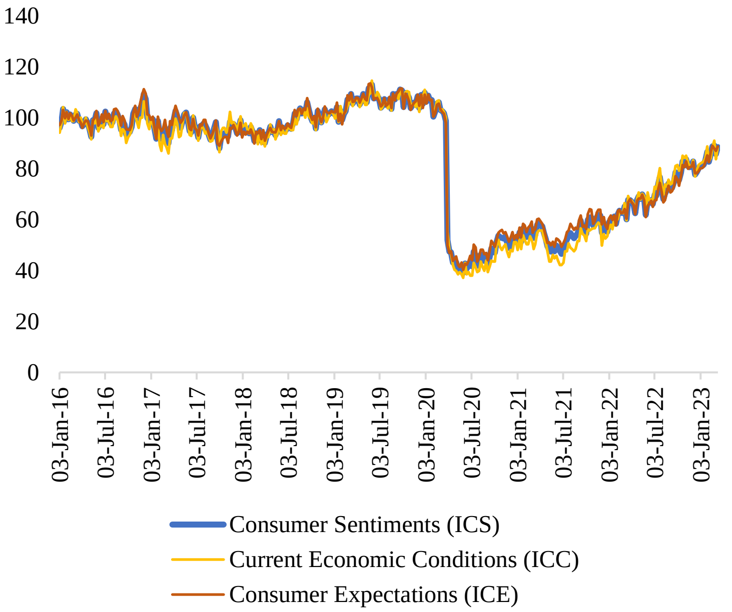
Note: Retail Payments include NEFT, UPI, IMPS, BBPS, CTS, AePS and NACH.

## Indicators wise Trends

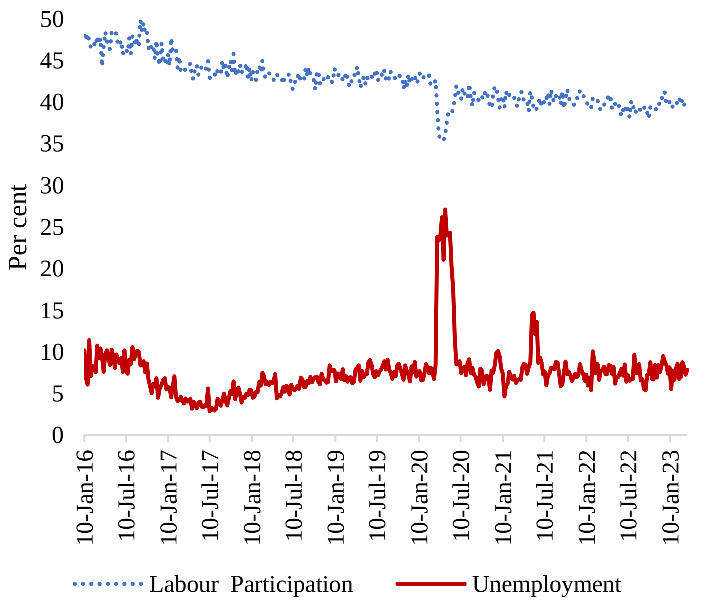
### Chart 1: Google Trends



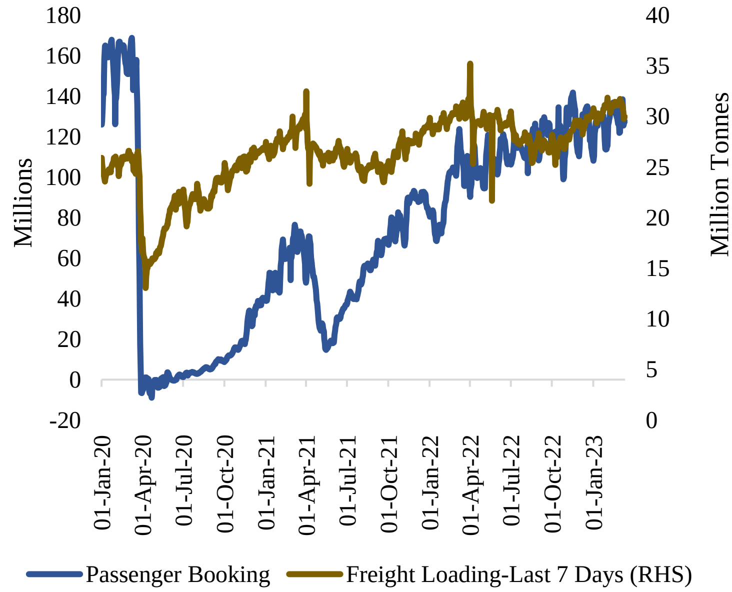

### Chart 2: CMIE Sentiment Indices




### Chart 3: CMIE Labour Market




### Chart 4: Rail Passenger & Freight




**Sources:** Google, CMIE and CEIC.

Labour market conditions are gauged through two indicators – unemployment rate and labour participation rate. Though, no long-term trend has been visible in the unemployment rate apart from the spike during the first and second waves, the labour participation has been following a gradual decline since the past few years (Chart 3). For inclusion in the model, inverse of unemployment rate has been considered to control for the inverse relationship between unemployment and output. In the transport sector, the passenger bookings and freight movement of the Indian railways also suffered a sharp decline on account of the pandemic and the related uncertainty, however freight movement registered a swift recovery (Chart 4).

**Chart 5: Registered Motor Vehicles**

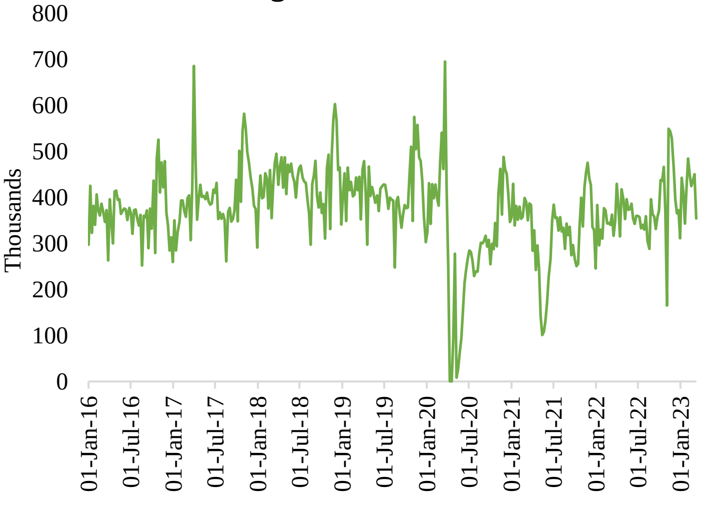
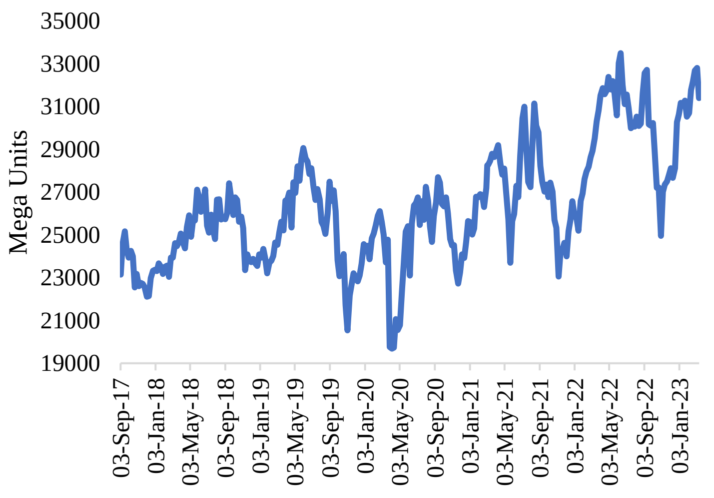
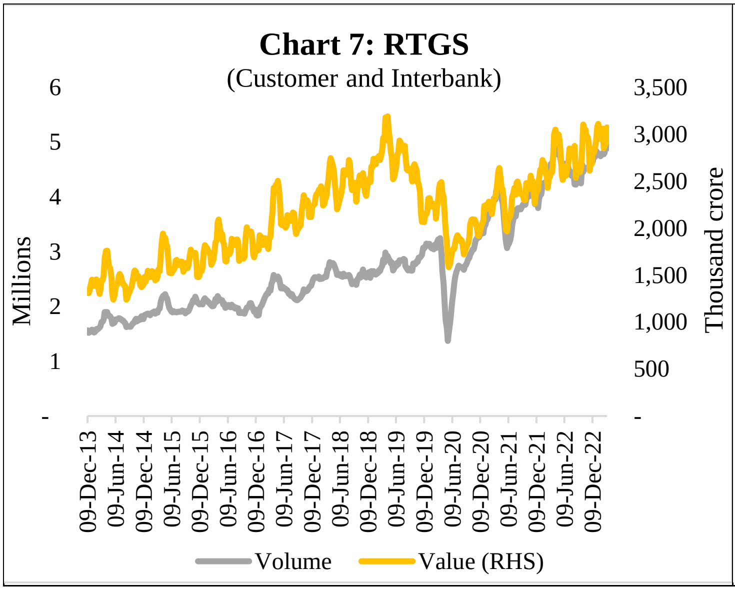


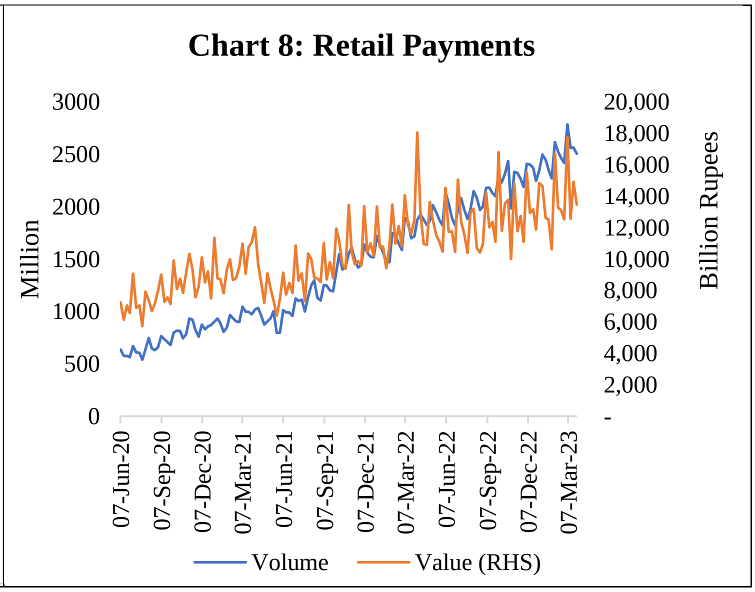

**Chart 6: Electricity Generation**




**Sources:** CEIC and Vahan Database.

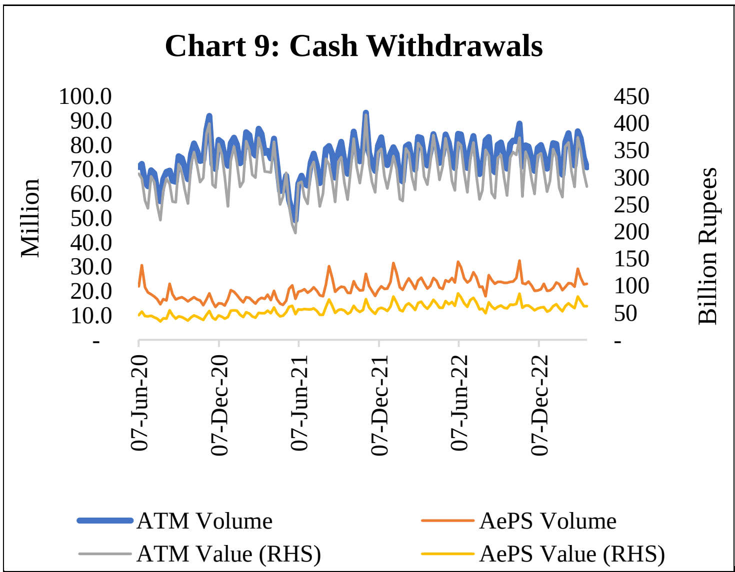
Weekly vehicle registration and electricity generation are two important indicators of the consumption demand. Though the vehicle registrations tend to peak near the festive season (particularly during October-November of each year), electricity generation tend to rise every summer season to meet the higher demand along with an upward trend over the past years (Chart 5 and 6).

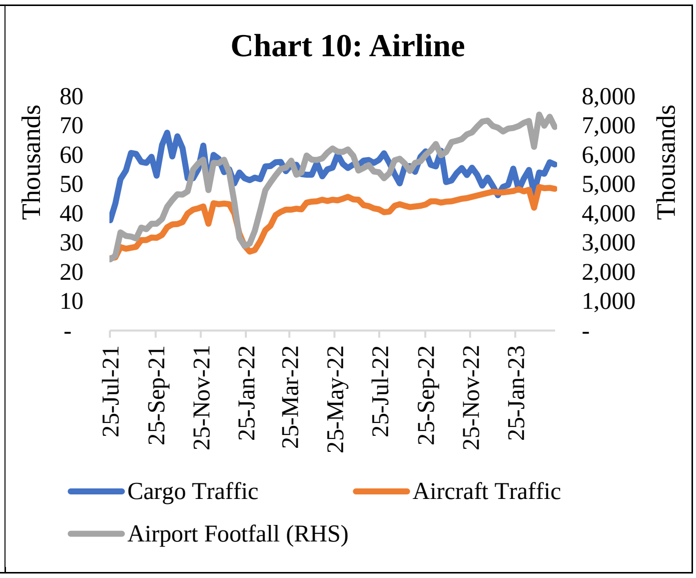



**Source**: RBI.

payments data made available and NPCI and RBI and represent an innovative source of tracing the underlying economic activity, given their crucial role in undertaking, and settling transactions in a market economy (RBI, 2021). Importantly, 98.5 per cent the total non-cash retail payments during 2020-21 were in the form of digital transactions. Volume and value of RTGS (customer and interbank) transactions has been on an upward trajectory for the past decade with the seasonal peak visible at every fiscal year end (Chart 7). Retail payments (value and volume) data which RBI began publishing since June 2020 also follow similar upward trend. With periodic payments being made at the end of every month, a jump is visible in both value and volume of retail payments (Chart 8). Despite suffering a blow during the pandemic both the data series have recovered quite well.



**Sources**: CEIC and RBI.

Since June 2021, data on the air cargo, aircraft movement and airport footfall has also been made available on daily basis. Although the period is too short to be considered for the DFM, these data series are used only in the diffusion index.

An examination of the stationarity properties of the indicators shows that majority of them are stationary at first difference (Table 4).

**Table 4: Inclusion of Indicators and their Stationarity Property**

| S. No. | Indicators | Diffusion Index | DFM – 7 | Stationarity |
|---|---|---|---|---|
| 1 | Google Trends | | √ | 1st Difference |
| 2 | Consumer Sentiment Index | √ | √ | Stationary |
| 3 | Unemployment Rate (%) | √ | √ | Stationary |
| 4 | Labour Participation Rate (%) | √ | √ | Stationary |
| 5 | Electricity Generation | √ | √ | 1st Difference |
| 6 | Motor Vehicle Registration | √ | √ | 1st Difference |
| 7 | Railway Freight Loading | √ | | 1st Difference |
| 8 | Air Cargo Traffic | √ | | 1st Difference |
| 9 | Railway Passengers | √ | | 1st Difference |
| 10 | Mobility (Retail, Grocery, Park, Transit & Workplace)* | | | Stationary |
| 11 | Aircraft Traffic | √ | | 1st Difference |
| 12 | Airport Footfall | √ | | 1st Difference |
| 13 | RTGS | √ | √ | 1st Difference |
| 14 | Retail Payments | √ | | 1st Difference |
| 15 | ATM and AePS Withdrawal | √ | | 1st Difference |

**Note:** Google Mobility indicators are included only in the weekly activity index presented in level terms to exhibit the impact of different Covid waves and subsequent resumptions in activities presented in Chart 3 in section 5.

The correlation coefficient between the growth rates of the indicators aggregated at monthly and quarterly frequency with y-o-y real GDP and IIP growth have been examined prior to their inclusion in the model. Indicators exhibited strong correlations with target variables with expected signs. The magnitude of correlation is particularly strong in case of RTGS payments, electricity generation, google trends and vehicle registration (Table 5a and 5b).

**Table 5a: Correlation Matrix: Y-o-Y growth in quarterly average Indicators and Real GDP**

| | Consumer Sentiments | LFPR | Unemp. Rate (Inv) | Electricity Gen | Vehicle Reg | RTGS | Google Trend |
|---|---|---|---|---|---|---|---|
| Consumer Sentiments | 1 | | | | | | |
| LFPR | 0.32 | 1.00 | | | | | |
| Unemp Rate (inv) | 0.26 | 0.56 | 1.00 | | | | |
| Electricity Gen | 0.37 | 0.12 | 0.52 | 1.00 | | | |
| Vehicle Reg | 0.34 | -0.23 | -0.29 | 0.54 | 1.00 | | |
| RTGS | 0.66 | -0.04 | 0.30 | 0.81 | 0.70 | 1.00 | |
| Google Trend | 0.63 | 0.33 | 0.58 | 0.78 | 0.34 | 0.57 | 1.00 |
| GDP | **0.74** | **0.40** | **0.56** | **0.84** | **0.53** | **0.85** | **0.80** |

**Table 5b: Correlation Matrix: Y-o-Y growth in Monthly Average of the Indicators and IIP**

| | Consumer Sentiments | LFPR | Unemp Rate (inv.) | Electricity Gen | Vehicle Reg | RTGS | Google Trend |
|---|---|---|---|---|---|---|---|
| Consumer Sentiments | 1 | | | | | | |
| LFPR | 0.28 | 1 | | | | | |
| Unemp Rate (inv.) | 0.21 | 0.49 | 1 | | | | |
| Electricity Gen | 0.33 | 0.15 | 0.47 | 1 | | | |
| Vehicle Reg | 0.20 | -0.09 | -0.03 | 0.57 | 1 | | |
| RTGS | 0.61 | 0.02 | 0.27 | 0.67 | 0.43 | 1 | |
| Google Trend | 0.58 | 0.31 | 0.52 | 0.76 | 0.31 | 0.51 | 1 |
| IIP | **0.44** | **0.14** | **0.29** | **0.86** | **0.84** | **0.74** | **0.64** |

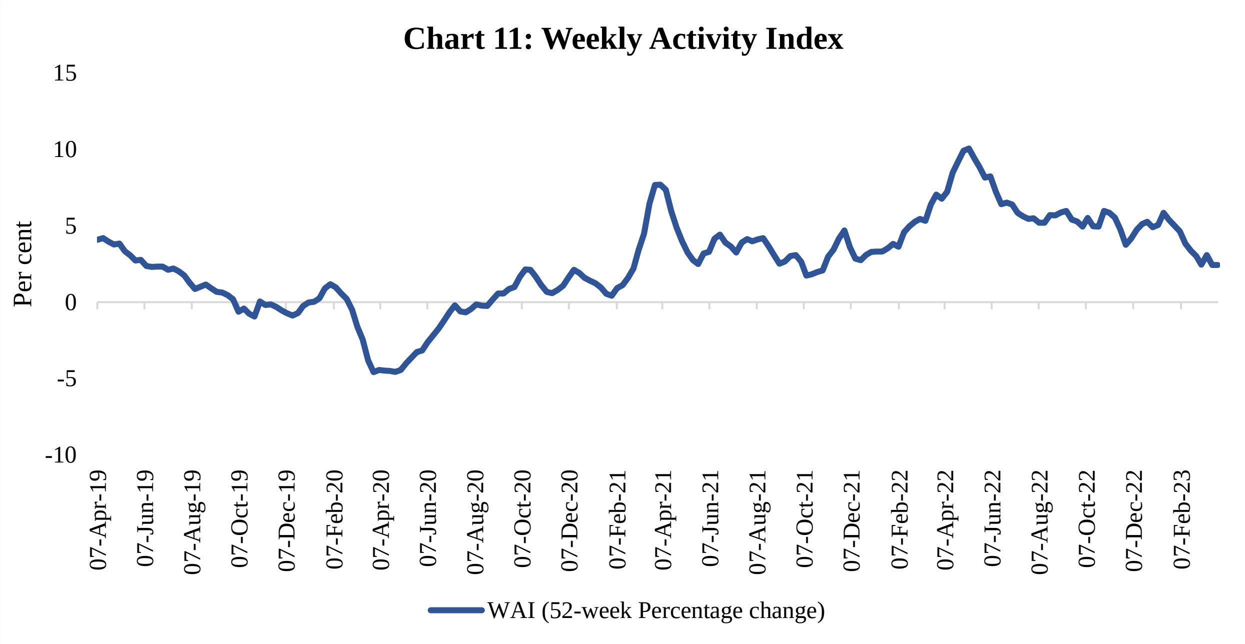
## V. Results

In this section, we first present the real time tracking and nowcasting of GDP based on the weekly indices followed by the nowcasting results from the FA-MIDAS model. Consistent with our earlier work (Prakash *et al.*, 2021), the seasonally adjusted auto regressive integrated moving average (SARIMA)[6] has been considered as a benchmark model against which the nowcasting performance of alternative models are compared. Nowcast performances are evaluated in terms of the root-mean-square error (RMSE), mean-absolute error (MAE) and Theil U statistic.

[6] ARIMA has been the traditional methodology widely used to model macroeconomic variables and also forecast GDP by identifying autoregressive and moving average terms. Since ARIMA is confined to only non-seasonal time series data, Seasonal ARIMA (SARIMA) – a more powerful methodology was developed which control for the seasonal pattern present in the variables concerned.

*Real Time Monitoring during the Pandemic Period*

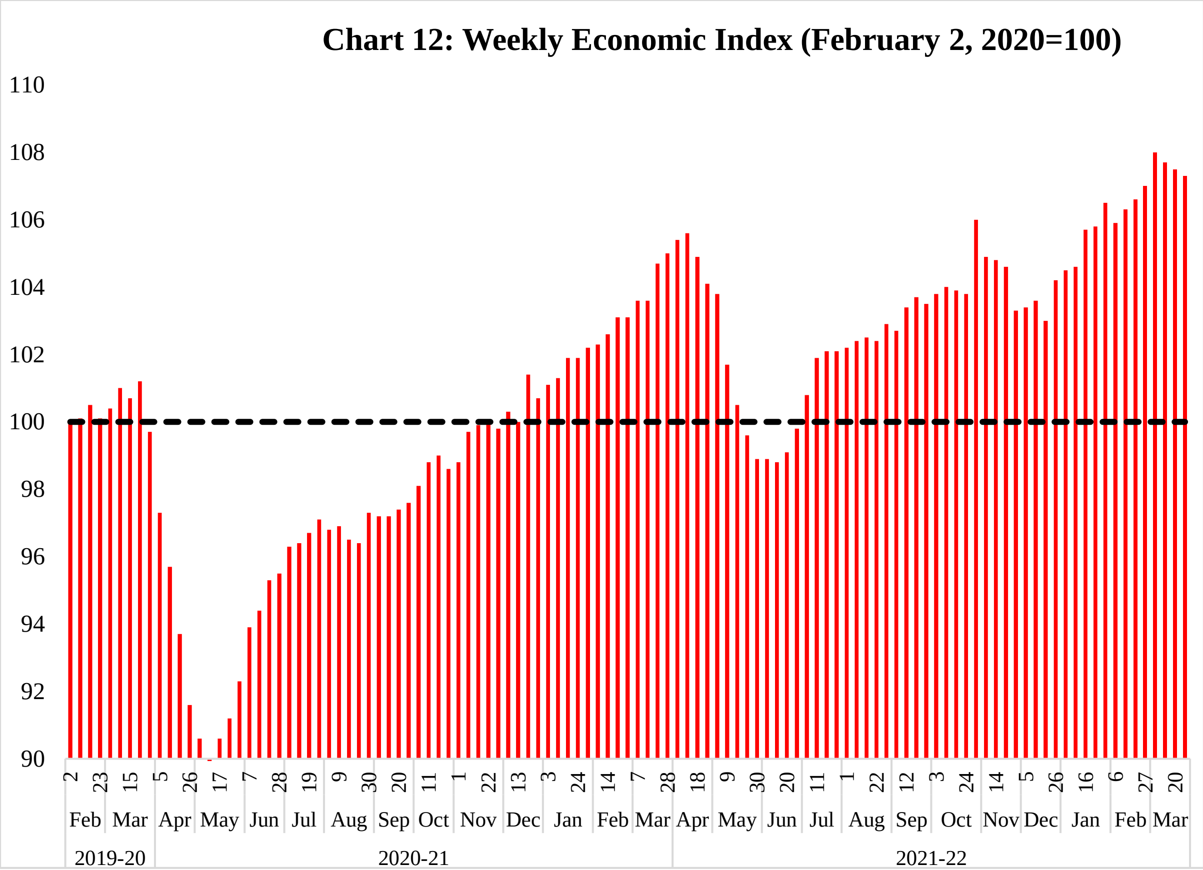
We attempt to relate the trajectory in WAI with the key events took place during the course of COVID-19 pandemic. On March 11, 2020, the WHO declared COVID-19 as a global pandemic. In India, the first case of COVID-19 was reported in Kerala on January 30, 2020 and since then India has experienced three waves of the virus so far, taking its total caseload to the second highest in the world. Likewise other countries, India also imposed strict restrictive measures to curb the spread of infections during the first wave. A nation-wide lockdown was announced on March 24 and continued till the end of May 2020. The WAI for the week ending on March 29 slipped to its lowest contracting by 9.6 per cent y-o-y and further declined in April and May 2020 (Chart 11). The contraction in WAI was underpinned by broad-based decline in almost all the constituent indicators such as consumer sentiments, electricity generation, vehicle registration, various search categories of google trend, RTGS payment and a skyrocketing in unemployment rate. The process of unlocking started since June 2020 in which restrictions were relaxed gradually, over 6 phases of unlocking - unlock 1.0 to unlock 6.0. Direct benefit transfers such as free ration per family members under the *Pradhan Mantri Garib Kalyan Yojna* followed by the *Atmanirbhar Bharat Abhiyan* aimed at protecting jobs, financial supports as well as regulatory relaxations, extensions, and guarantee schemes restored V-shaped recovery in some indicators such as RTGS transaction, electricity generation, unemployment, and labour force participation rates. Consumer sentiments, railway, air travel, vehicle registration improved at a slower pace.




**Source**: Author's Estimates.

The WAI approximate year over year changes had been heavily influenced by base effects in 2021-22 emanating from the sharp contraction in 2020-21 and, therefore, obscured the subsequent impact of the COVID-19 waves in 2021-22. To address this issue, a weekly recovery index which is at levels was developed, curated specifically for economic impact of different waves of the pandemic vis-à-vis. the pre-pandemic level. The weekly recovery index[7], surpassed its pre-pandemic level since the first week of December 2020 and was sustained there for fifteen successive weeks till the second week of April, 2021- the period when the second wave intensified (Chart 12). The impact of the second wave was less severe compared to the first wave but distinct from the trajectory of the recovery index which moderated below its pre pandemic level since the third week of April 2021. Unlike the first two waves of COVID-19, the Omicron wave did not have any significant adverse economic impact as the recovery index remined above 100 (*i.e.,* the pre-pandemic level) in December and January 2022 and rebounded swiftly to an upward trajectory thereafter.

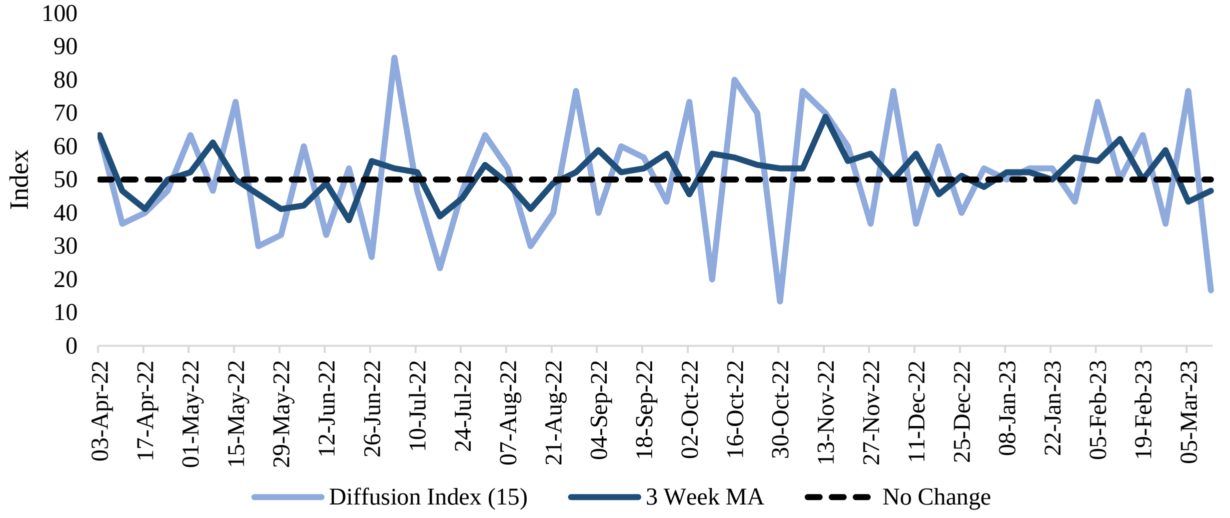
[7] The weekly recovery index was developed specifically to measure the extent of dip in economic activity across various waves of COVID pandemic. With the receding of the third wave in the early 2022 and no further occurrences of COVID waves, this index has been discontinued.




**Source**: Author's Estimates**.**

The Russia-Ukraine war declared on February 24, 2022, caused another major disruption to economic recovery. The WAI recovered following a downturn during January caused by the Omicron wave. WAI registered double-digit growth on average in the month of April and May 2022. However, the sharp uptick seen in these two months were partly due to the base effect emanating from the second wave affected weeks in the previous year, *i.e.,* 2021. WAI in the subsequent quarters Q2 and Q3:2022-23 moderated as also reflected in their GDP estimates. The sequential movement evident from the weekly diffusion index (WDI) suggests sluggishness in momentum in the first half of 2022-23 amidst the multiple headwinds such as a surge in commodity prices leading to accentuated input cost pressures, supply side disruptions and global slowdown (Chart 13). The index, however, showed improvement since November 2022 and remained resilient before moderating again in March 2023.

**Chart 13: Weekly Diffusion Index**




**Source**: Author's estimates.

*Nowcasting Using Weekly Indicators*

The WAI - aggregated over a quarter, available within a week after the end of a reference quarter and nearly two months before the official release of GDP data, also produce a nowcast of GDP for the corresponding quarter. These nowcasts have been observed to be in the vicinity of the official estimates. Following contractions in the first two quarters, the WAI rebounded to positive territory in the third quarter and strengthened further in the fourth quarter of 2020-21 mirroring similar trend as observed in GDP estimates. Thus, the WAI followed the ebbs and flows in economic activity during the pandemic year reasonably well. For the latest quarter Q3:2022-23 for which official estimates of GDP are available, the nowcast from aggregated WAI came dot at 4.9 per cent as the NSO estimate.

We further explore the predictive relationships between the WAI and lower-frequency real activity measures since such forecasts are a natural application of the WAI. We attempt to nowcast[8] the target variable GDP by regressing the flow of information from the WAI, starting with the WAI for just the first month of the quarter and so on.

$$GDP^q\ growth = \mathrm{c} + \sum_{i=1}^{mi} \beta_i\, WAI_q^{mi} + e_q;\ \mathrm{mi} = 1,2,3; \qquad (2)$$

[8] The standard nowcasts (including those of the Federal Reserve Banks of New York, Atlanta and St. Louis) focus on lower frequency targets like GDP growth, which are very informative about the economy. But, since GDP is a quarterly variable, such models are not equipped to highlight variation from one week to the next.

The goal of these nowcasts is only to predict average variation in the target series over the frequency of the target variables which it performs well. For quarterly GDP, the WAI for all the three months is highly significant (Table 6). However, the first month presents the strongest relationship with the highest value of adjusted R-square which decreases slightly over the next two months.

**Table 6: Monthly Information-flow**

| | WAI Month 1 | WAI Month 2 | WAI Month 3 |
|---|---|---|---|
| **Coefficient** | 0.952 | 1.034 | 0.990 |
| **Standard Error** | 0.164 | 0.195 | 0.235 |
| **P-Value** | 0.00005 | 0.000113 | 0.00086 |
| **Adjusted R-square** | 0.685964 | 0.64311 | 0.52790 |
| **F Statistics** | 33.7652 | 28.0304 | 17.7730 |
| | 0.000045 | 0.000113 | 0.00086 |
| **No. of Observations** | 16 | 16 | 16 |

*Nowcasting Results for FA-MIDAS*

In Prakash *et al*., (2021) the DFM based nowcasting using monthly indicators were estimated for a period spanning Q1:2005-06 to Q4:2019-20. The WAI developed in Prakash *et al*., (2022) started from a more recent period since Q3:2018-19 as data on daily/weekly indicators started to become increasingly available since around 2017-18. The set of daily/weekly indicators is still expanding as several new series have been started releasing only after the pandemic. For example, data on payment systems, aviation sector etc. started only since 2020. In our current exercise, we have used both monthly and weekly variables in a FA-MIDAS model as the predictors for quarterly GDP. Constrained by the number of observations in the weekly variables, the estimation of the FA-MIDAS model[9], has been limited to a shorter period for

[9] One limitation of MIDAS model is that it cannot handle missing observations. Therefore, the observation period has to be restricted depending upon the availability of weekly indicators.

Q3:2018-19 to Q3:2022-23. For evaluation of nowcast performance, the total sample has been divided in 70:30 ratio into training sample (Q3:2018-19 to Q2:2021-22) and testing sample (Q3:2021-22 to Q3:2022-23).

**Evaluation of Nowcast Performance**

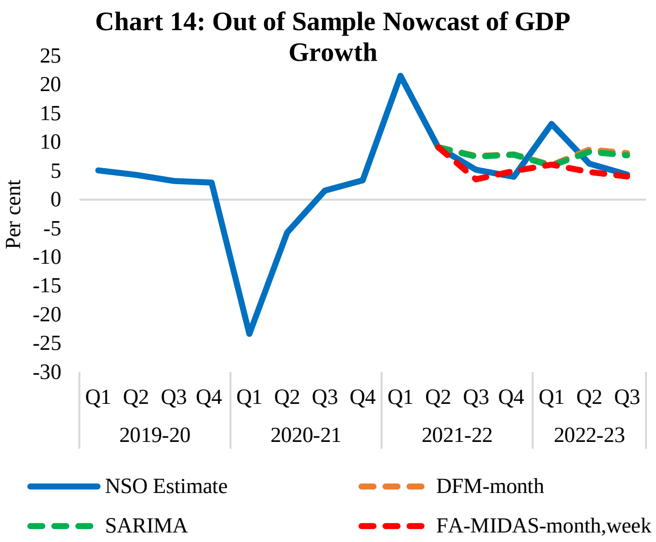



**Table 7: Out of Sample Nowcast Performance (Q3:2021-22 - Q3:2022-23)**

| | RMSE | MAE | Theil's U |
|---|---|---|---|
| **FA-MIDAS-month, week** | 3.37 | 2.35 | 0.74 |
| **SARIMA** | 3.90 | 3.43 | 0.79 |
| **DFM-month** | 4.01 | 3.54 | 0.8 |
| **Pre-pandemic (Q1:2005-06 - Q4:2019-20)** | | | |
| **SARIMA** | 1.35 | 0.98 | 0.52 |
| **DFM-month** | 0.96 | 0.41 | 0.44 |

In the pre-pandemic period, the out of sample nowcast from the DFM model show significant improvement in out of sample nowcast error over the benchmark SARIMA model. In the post pandemic period, however, due to, huge break in the general trend of the indicators, the nowcast error of all class of models has shot up. In alternative models considered in our exercise, out of sample nowcast errors reported to be larger in the post pandemic period than that in the pre-pandemic period. However, the FA-MIDAS model exhibits the lowest nowcast errors in the post pandemic period, thus justifying the value addition from including weekly variables into the standard nowcasting models (Chart 14 and Table 7).

## VI. Conclusion

In the backdrop of the one of its kind of the COVID pandemic shock, the motivation of the current exercise was to adapt and upscale our pre-existing nowcasting models which appear inadequate in reflecting the atypical changes in the economy. As information that feeds into the econometric model became inadequate, projection exercise during and post pandemic saw increased dependence on qualitative judgement, adjustments in the model specification and use of additional data. In this paper, we tried to extend our existing nowcasting model which is based on monthly indicators to include additional data in the form of daily/weekly indicators. With more frequent and up to date dataflow, the daily/weekly indicators allow model-based monitoring of economic activity to be more real time, thus enhancing their relevance for policy making. We develop a FA-MIDAS model by integrating two composite indices – at monthly and weekly frequency, respectively, constructed using the dynamic factor model for the purpose of nowcasting quarterly GDP.

Regarding the real time monitoring based on weekly indicators, the WAI appears to be very useful activity tracker during the pandemic period amid fast changing economic and policy environment. The WDI for a week depicts the momentum in economic activity in terms of a single index value. Moreover, the 13-week moving average of the scaled WAI produce reasonably close nowcast of GDP of a reference quarter immediately at the end of the quarter.

The FA-MIDAS model, which is well equipped to incorporate variables at multiple frequencies (quarterly, monthly, and weekly in our case), exhibits the lowest nowcast errors in the post pandemic period, thus justifying the value addition from including weekly variables into the standard nowcasting models. However, in alternative models considered in our exercise, out of sample nowcast errors reported to be larger in the post pandemic period which happened to be a common case across the globe as reported in the post pandemic nowcasting literature.

Presently, the set of daily and weekly high frequency indicators is limited but growing at a fast pace since the outbreak of the pandemic. Some of the crucial variables such as daily airport footfalls, air cargo movement, retail payments etc., are available for a very short duration and could not be included in the model-based WAI. The limited observations in weekly indicators appeared as a binding constraint in our current exercise as the FA-MIDAS model[10], must be restricted to a much shorter period than what is required for meaningful statistical interpretations. This not only curtailed our flexibility in terms of model specifications, but also increases the risks of problems like overfitting. Nonetheless, within its limitations, the model helped addressing the problem of large forecast error post pandemic by reducing the margin of error in the existing standard models.

[10] One limitation of MIDAS models is that they cannot handle missing observations. Therefore, the observation period has to be restricted depending upon the availability of weekly indicators.

Unlike the advanced economies, in India, where the data availability of data started growing only in recent times, the data driven model-based exercise are at relatively nascent stage. Going forward, with availability of sufficient data points and improved coverage with newly available indicators, the model performance would certainly gain precisions and robustness for policy making.

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