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Kaustubh NA
Reserve Bank of India, India, kaustubh@rbi.org.in

Soumya Suvra Bhadury
Reserve Bank of India, India, soumyasbhadhury@rbi.org.in

Saurabh Ghosh
Reserve Bank of India, India, saurabhghosh@rbi.org.in

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REINVIGORATING GVA NOWCASTING IN THE POST-PANDEMIC PERIOD: A CASE STUDY FOR INDIA

Kaustubh*, Soumya Bhadury**, and Saurabh Ghosh***

*Corresponding author. Reserve Bank of India, India. Email: kaustubh@rbi.org.in[1]
**Reserve Bank of India, India. Email: soumyasbhadury@rbi.org.in
*** Reserve Bank of India, India. Email: saurabhghosh@rbi.org.in

ABSTRACT

We reinvigorate nowcasting models considering structural changes caused by the COVID-19 pandemic. It emphasizes the need to understand the heterogeneous impact of shocks on agriculture, industry, and services sectors in an emerging market economy, such as India. Our findings advocate a bottom-up approach that tracks sectors separately rather than a headline number. Our results suggest that including digital-activity index and supply-side disruption index in the post-pandemic period could improve nowcast performance. Expectation-Maximization algorithm is used to combine data series based on their availability. Among bridging methods, the averaging method is preferred due to its simplicity and flexibility.

Keywords: Gross value added; Dynamic factor; Coincident economic activity index; Digital payments; Mixed data sampling (MIDAS).
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I. INTRODUCTION

Central bank's monetary policy is forward looking and requires knowledge of the current state of the economy. But the official estimates of the key macroeconomic variables come with a lag and to bridge this gap, central banks have increasingly adopted nowcasting models to offer prompt, forward-looking, and policy-relevant insights into key macroeconomic variables such as GDP. In this regard, nowcasting has become an important tool as it involves estimating a target variable in the present or the near future based on available High Frequency Indicators (HFIs) before the release of official estimates. Such HFIs contain information about the target variable before the release of official estimates. Thus, nowcasting is fundamentally different from forecasting as it focuses on measuring the current state of the target variable. These model-based nowcasts are employed by various central banks, including the Bank of England, the Federal Reserve Banks of Atlanta (FRBA), and New York (FRBNY), which publish their own model-based nowcasts. Additionally, other prominent central banks such as the European Central Bank, the Norges Bank, and the Reserve Bank of India utilize nowcasting models alongside their regular predictions to enhance their forecasting capabilities.

Nowcasting models rely on many HFIs over an extended period, making them data dependent. Nevertheless, the data-generating processes have been significantly disrupted by the COVID-19 pandemic, posing a challenge to the models in extracting prevailing trends. Additionally, new data sources have emerged as important indicators during and after the pandemic, such as E-way bills, mobile connectivity, ATM-PoS withdrawal, and Google mobility data. However, these series lack the long time-series data required by traditional nowcasting and dynamic forecasting models. To address this issue, we adopt the Expectation-Maximization (EM) algorithm in our dimension reduction technique to combine data series with different vintages based on their availability, see Bhadury *et al*. (2021).

Despite India's long history of tracking and nowcasting headline GDP (Bhadury *et al*. (2021); Bhadury *et al*. (2020)) there has been little research on tracking Gross Value Added (GVA) at the sectoral level.[2] There are a few exceptions, such as the work by Roy *et al*. (2016), which primarily focused on the pre-pandemic period. Given the importance of agriculture, industry, and services to India's economic growth, it is critical to monitor sectoral activity. This is especially important given the significant changes in India's economy[3], with the service sector taking centre stage. Given these constraints, we address variable selection by prioritising their sectoral significance and reducing dimensions to avoid overfitting. Tracking sectoral heterogeneity on a regular basis can help inform effective policies that promote long-term, inclusive economic growth.

[2] GVA at basic prices is used as a target measure because it represents the value added of all goods and services produced in an economy. GVA at basic prices is comprised of three major sectors: agriculture, industry, and services, making it a comprehensive measure of the economy's performance. Quarterly GVA is tracked by using a carefully selected set of HFIs to project the year-on-year growth rates of various GVA sectors, namely agriculture, industry, and services. The paper contributes to the growing literature on nowcasting by attempting to apply existing frameworks to Indian high-frequency data in the post-pandemic period. The paper finds a significant improvement in forecast precision over naive models when using the nowcasting framework.

[3] The study is focused on nowcasting GVA of the Indian economy only, however the methodology used in the study is flexible and can be adopted for other countries.

Given India's advancements in digital technologies and the real-time availability of related datasets, we combine multiple data series on digital payments while constructing a digital index for India. We test if an inclusion of such a digital index in our nowcasting model improves the model performance. To be precise, we compare the model's performance after inclusion of the digital index in both pre-pandemic and post-pandemic periods. Our findings reveal significant improvements in the model's performance, during the post-pandemic period, thus demonstrating that digital inclusion leads to significant improvements in forecasting economic activity in India. Given the rapid development of digital payments in India, we are of the view that the digital block could become an essential component of future nowcasting models.

The revival of India's economy following the COVID-19 pandemic has been impeded by significant disruptions in the global supply chain. This paper aims to assess the impact of these disruptions on nowcasting exercise by employing an innovative index tailored to quantify the costs associated with such disruptions. Referred to as the Global Supply Chain Disruption Cost Index (GSCDCI), this index utilizes a dynamic factor model to extract a shared factor from four key monthly indicators: the Baltic Dry Index, Bloomberg Commodity Index, IMF Fuel (Energy) Index, and Semiconductor Equipment Billing (Bhadury *et al*. (2023)).

Finally, we employ the mixed data sampling (MIDAS) technique within the framework of the bridge equation model to establish a connection between low-frequency dependent variables and a higher-frequency activity index. To assess and compare the efficacy of various bridging methodologies, namely Bridge, Almon MIDAS, and U-MIDAS, an out-of-sample evaluation was conducted. The findings of this study suggest that no definitive bridging methodology emerged as the superior choice, as the results exhibited variability across different periods and target variables. Nevertheless, owing to its simplicity and flexibility, the Bridge method can be considered advantageous compared to more intricate bridging techniques, such as Almon MIDAS and U-MIDAS.

In the remainder of the paper, we emphasize the need to re-examine prominent nowcasting models. The paper is organized as follows: Section II provides a brief review of the existing literature, Section III outlines the data and methodology, Section IV critically evaluates our empirical findings, and Section V concludes.

II. LITERATURE

The use of economic activity indicators in the GDP nowcast has a long history in advanced economies and is still actively used in monetary policymaking by many of the central banks. Perhaps the first use of such indicators is found in Burns and Mitchell (1946), which popularized the study of business cycles and eventually led to the creation of the composite index of coincident indicators. The methodology has gradually been refined over time, with the initial set of studies using non-parametric methodologies (e.g., principal component analysis). Thereafter, a breakthrough came in Stock and Watson's (1989) seminal work on estimating a single-index Dynamic Factor Model (DFM). Thereafter, DFMs dominated the nowcasting literature and outperformed the naïve, autoregressive, and PCA-based models. More recent literature, pioneered by Giannone, Reichlin, and Small

(2008), used DFM based on many high-frequency indicators, and such models had been the workhorse for macroeconomic nowcasting across advanced economies.

The application of high-frequency variables in GDP nowcasting is relatively new in emerging market economies and has been challenged by small sample sizes, non-synchronous data releases, and varying data lags. Here, seminal work by Ghysels, Santa-Clara, and Valkanov (2004) on the mixed data sampling (MIDAS) method has been very useful. It is a regression-based method that uses a weight structure to transform high-frequency data into low-frequency indicators, and higher weights are assigned to the recent observations as compared to the older observations. The EM algorithm is also useful in analysing non-synchronous data releases that are often observed in EMEs. Two noteworthy papers that use a bridge-equation framework are Luciani *et al*. (2015) for Indonesia and Caruso (2015) for Mexico, which used maximum likelihood estimation in an Expectation-Maximization (EM) algorithm for constructing an economic activity index.

India has made an early beginning in the nowcasting research. For instance, see Banerji and Dua (2001) and the Technical Advisory Group constituted by the Reserve Bank of India (2007). Banerji and Dua (1999) published an index of monthly coincident indicators to help ascertain the timing of recession and expansion of economic activity based on a set of objective indicators that are synchronous with cyclical fluctuations in growth. In one of the frequently quoted articles, Bhadury *et al*. (2021) extensively analysed different nowcasting methods using an Indian dataset. It found empirical evidence that suggests that the dynamic factor-based nowcasting model augurs well with a set of carefully curated pre-pandemic high-frequency Indian datasets. Ghosh and Ranjan (2023) used the same set of high-frequency indicators and applied machine learning techniques to find possible improvements in the nowcasting performances. Further, Roy *et al*. (2016) attempt to use the available information sets, Giannone's methodology, and the stochastic volatility approach (Feroni and Marcellino (2013)) for forecasting non-agricultural GVA for India.

It is important to note that in terms of sectoral GVA nowcasts, it is extremely challenging to nowcast agriculture's growth using HFIs as it is highly seasonal and on account of paucity of high-frequency data pertaining to crop production. In fact, there is no indicator available for livestock, forestry, and fishing – which have a share of 46 per cent in overall agriculture GVA in 2021-22. Additionally, the performance of agricultural sector is driven by external factors, such as rainfall, sowing patterns, and reservoir status. These factors can significantly impact the output of the agriculture sector, making it challenging to accurately measure the growth rate of the sector at a higher frequency, see Roy *et al*. (2016).

As discussed earlier an accurate and timely assessment of current economic activity is of paramount importance to policymakers and decision-makers, influencing crucial aspects such as the implementation of countercyclical policies and short-term production decisions. However, the primary metric used to gauge economic activity, namely GDP growth, is released with a significant time lag (two months in the case of India) and is subject to notable revisions. Consequently, policymakers necessitate reliable estimations of current-period GDP growth, commonly referred to as "nowcasts," to effectively monitor economic conditions. In this context, the present study makes a noteworthy contribution by investigating

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an expansion of the information available to nowcasters. Specifically, we compile and analyze a comprehensive database encompassing transactions processed through the payments system. This database provides valuable insights into the values and volumes of debit and credit card transactions, as well as the clearance of cheques through the banking system (Galbraith and Tackz (2015)).

The COVID-19 pandemic indeed marked a breakpoint in this ongoing literature and questioned the nowcasting techniques that depend on long-term stable data generation processes or overemphasized the recent observations-based methodology.[4] Notwithstanding the Ukraine war, with the gradual recovery of economic activities, researchers have started analysing the pandemic cracks and suggesting ways to bridge them. One such attempt for Latin American countries is undertaken by a recent World Bank working paper (Bravo *et al*. (2020))[5] It makes use of daily mobility and air quality data to predict movements in industrial production. While the results of the paper indicate reasonable success in the earlier days of the pandemic during the restricted mobility phase due to pandemic related restrictions. However, mobilities have mostly returned to the pre-pandemic state in most of the economies, which raises doubt on the efficacy of the above-mentioned variables in nowcasting current economic growth. Huber *et al*. (2023) have tackled the similar problem of pandemic related disruption using non-parametric mixed frequency techniques such as mixed frequency vector auto regression methods to address extreme fluctuations in the GDP number during the pandemic. The use of these techniques allowed for modelling outliers observations in the data observed during pandemic disruptions.

Thus, there are several challenges faced while nowcasting GDP during uncertain events such as COVID-19. In this regard, we have tried to fill the gap by exploring efficacy of addition of COVID-19 dummy in the bridge equation and introduction of Global Supply Chain Disruption Index (GSCDCI) in nowcasting exercise in the post pandemic period to account for disruptions and uncertainty of the post pandemic period. We have also explored that if mixed frequency techniques such as MIDAS and U-MIDAS improve the nowcasting performance over simple averaging of high frequency monthly indicators to quarterly frequency for Indian sectoral GVA during the growth fluctuations of pandemic period.

Over the past five years, the digital payment landscape in India has witnessed significant advancements through the introduction of user-friendly and convenient modes of transactions. Prominent among these modes is Bharat Interface for Money-Unified Payments Interface (BHIM-UPI), Immediate Payment Service (IMPS), and National Electronic Toll Collection (NETC). These digital payment platforms have played a transformative role in facilitating both person-to-person (P2P) and person-to-merchant (P2M) transactions, thereby revolutionizing the digital payment ecosystem. BHIM UPI has gained substantial popularity among citizens, emerging as their preferred mode of payment. In January 2023 alone, BHIM UPI recorded an impressive volume of 803.6 crore digital payment

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[4] For surveys of the COVID-19 literature, see Narayan (2021), Phan and Narayan (2020), Sharma and Sha (2020), and Sha and Sharma (2020), amongst others.

[5] Bravo, S., Ezequiel, J. R., & Jooste, C. (2020). Nowcasting Economic Activity in Times of COVID-19: An Approximation from the Google Community Mobility Report. *World Bank Policy Research Working Paper*, No. 9247.

transactions, with a total value amounting to ₹12.98 lakh crore. The growth of Digital Payments in India and the availability of various easy and convenient digital payment solutions have facilitated ease of living for citizens, financial inclusion, and growth of business and economy.[6] The benefits of using digital payments in India are summarised in Table 1. Anecdotal evidence suggests that during the lockdowns, the digital economy picked up in a very big way, and it has continued to be buoyant since then.

Table 1.
Benefits of Digital Payments in India

This table presents lists various benefits of digital payments in India.

Benefits of Digital Payments	Description
Instant and convenient payment	Transfer money instantly using BHIM-UPI and IMPS. Access multiple bank accounts with one app for easy payments.
Enhanced financial inclusion	Gain anytime, anywhere access to accounts for receiving and making payments. UPI promotes rural financial inclusion.
Increased transparency in government	Directly transfer benefits to target accounts, eliminating leakage and ghost recipients.
Improved speed and timely delivery	Enjoy near-instant transactions regardless of location.
National Electronic Toll Collection	Make hassle-free toll payments using the NETC system's RFID technology.
Bharat Bill Payment System	Conveniently settle bills through multiple channels with the Bharat Bill Payment System (BBPS).
Enhanced Credit Access	Build a financial footprint for better access to credit.
Safe and secure	Ensure secure transactions with multi-layer authentication.

In this paper, we, therefore, leveraged this digital transformation and used sectoral segregation in our forecasting model. While adding this new dimension, we are also mindful of the traditional indicators and attempt to strike an optimal balance that could significantly improve our post-pandemic nowcasting performances.

III. DATA AND METHODOLOGY

A. Data Set

The use of GVA at basic prices as a measure for nowcasting is based on the fact that it represents the value added of all goods and services produced in an economy. The three major sectors that constitute GVA at basic prices are agriculture, industry, and services, which make it a comprehensive measure of the economy's performance.

GVA data is available only from Q2 of 2011 following the rebasing exercise by the NSO. The rebasing exercise changed the base year for calculating national accounts statistics from May 2004 to December 2011. To address this issue, a splicing technique was used to construct the back series of GVA at basic prices.

[6] Digital Transaction in India, Ministry of Electronics and IT; Retrieved from https://www.pib.gov.in/PressReleasePage.aspx?PRID=1897272

This method estimates a longer GVA series for agriculture, industry, and services by deriving a long time series of quarterly GVA with base year 2011/2012 by using a simple splicing of the published national accounts series for 2004/2005.

The estimation of quarterly GVA is done using a set of chosen HFIs to project the year-on-year growth rates of various GVA sectors; namely agriculture, industry, and services listed in Table 2.[7] In addition to these three blocks, we have used high-frequency indicators to track a general activity bloc, specifically focusing on digital transactions, etc., and a block to track the global supply chain disruptions represented by indicators focusing on global supply chain pressures. The sectoral GVA estimates are then combined to determine the overall GVA estimate. Table 2 lists the HFIs utilized by this study in nowcasting the sectoral GVA.

Table 2.
High-frequency Indicators and their Frequency

This table presents the list of HFIs used in study construct Agriculture, Industry, Services, Digital Activity Indices along with GSCDCI.

Sectors	High-frequency Indicators	Frequency	Source
Agriculture	Fertiliser Sales	Monthly	Department of Fertilizers
	Tractor Sale	Monthly	Tractor and Mechanization Association
	Rainfall Actual	Daily	India Meteorological Department
	Rainfall Deviation	Daily	India Meteorological Department
	Two-wheeler Sales	Monthly	Society of Indian Automobile Manufacturers
Industry	Cement Production	Monthly	Ministry of Commerce and Industry
	Container Traffic	Monthly	Indian Ports Association
	Crude Steel	Monthly	Joint Plant Committee
	IIP Core	Monthly	Ministry of Commerce and Industry
	IIP Electricity	Monthly	Ministry of Statistics and Programme Implementation
	Non-oil non-gold Imports	Monthly	Ministry of Commerce and Industry
	PMI Manufacturing	Monthly	S&P Global
	Non-oil Exports	Monthly	Ministry of Commerce and Industry
	Coal Production	Monthly	Ministry of Commerce and Industry
	Rail Freight	Monthly	Indian Railways
Services	Air Cargo	Monthly	Airports Authority of India
	Air Passenger	Monthly	Directorate General of Civil Aviation
	Insurance (Non-life)	Monthly	Insurance Regulatory and Development Authority of India
	Rail Freight	Monthly	Indian Railways
	Rail Passengers	Monthly	Indian Railways
	PMI Services	Monthly	S&P Global

[7] The sectoral classification used in the study in terms of Agriculture, Industry, and Services are based on NSO classification of GVA sub-sectors. However, it is slightly different from NSO sectoral classification of economy in terms of primary, secondary and tertiary sectors. Primary sector consists mainly of agriculture and allied activities but also includes mining and quarrying which is part of Industry. Secondary sector comprises of manufacturing, electricity, gas, water supply & other utility services and construction, which are part of industry. Tertiary sector comprises all services, which is part of services sector.

Table 2.
High-frequency Indicators and their Frequency (Continued)

Sectors	High-frequency Indicators	Frequency	Source
Digital (General Activity)	Card Payment	Daily	Reserve Bank of India
	Digital Payment	Daily	Reserve Bank of India
	Electronic Toll	Daily	Reserve Bank of India
	Eway Bill	Daily	Goods and Services Tax Network
	Mobile Payments	Daily	Reserve Bank of India
	NPCI Retail Payment	Daily	National Payments Corporation of India
	Payment Instrument	Daily	Reserve Bank of India
	RTGS	Daily	Reserve Bank of India
Global Supply Chain Disruption Cost Index (GSCDCI)	Baltic Dry Index	Monthly	Baltic Exchange Information Services Limited
	Bloomberg Commodity Index	Monthly	Bloomberg
	IMF Fuel (Energy) Index	Monthly	IMF
	Semiconductor Equipment Billing	Monthly	Semiconductor Equipment and Materials International

B. Methodology

The nowcasting exercise in this study starts with identifying sets of relevant HFIs from a large set of potential HFIs. We have selected the HFIs by checking the correlation between the momentum of HFIs and sectoral GVAs. The methodology and findings of the HFIs selection procedure are explained in detail in the empirical finding section.

After identifying the relevant variables, the next step is to construct a Dynamic Factor Model (DFM) that reflects the common trend underlying these variables. In recent research, the DFM has been used to extract the common component of variability across several variables (see Stock and Watson, 1989; 2002; Giannone *et al*., 2008). In this scenario, the DFM is estimated using a local-level representation of the overall state-space form. The DFM observation equation includes a matrix of economic indicators at time t, which is used to extract the common underlying trend as a single-index dynamic factor. At time t, the DF has a dimension of $m\times1$ and is represented as a linear combination of the observed variables and factor loadings, plus an offset term. The factor loading is a matrix of dimensions $n*m$.

$$x_t = B * x_{t-1} + w_t \; where \; w_t \sim MVN\,(0, Q) \tag{1}$$

$$y_t = Z * x_t + a + v_t \; where \; v_t \sim MVN\,(0, R) \tag{2}$$

$$x_0 \sim MVN\,(\Pi, \Lambda) \tag{3}$$

The hidden trend's process is represented in Equation (1), w_t representing the process error and Q representing the covariance structure of the process error, which has a size of $m*m$ in the current specification. The matrix R reflects the covariance structure of observation errors, while the matrix x_0 represents the starting state vector. In this work, the DFM employs the Multivariate AutoRegressive State-Space (MARSS) specification, which includes two stochastic components: an unobservable common component and an idiosyncratic component. The Dynamic Factor (DF) for the industry bloc i.e. DF-Industry, for example, incorporates eleven observable time series: air cargo, cement production, container traffic, crude steel, IIP-core, IIP-electricity, non-oil and non-gold imports, PMI manufacturing, non-oil exports, coal production, rail freight. The identifying assumption in the above model is that the co-movements in the time series indicators arise from a single source, i.e., x_t enters each indicator with different loadings, z_i=1,2,⋯,11. This is ensured by our assumption that v_{it} and x_t are mutually uncorrelated at all leads and lags for all six observed economic indicators. The same model is used to estimate three other blocs DF-Agriculture, DF-Services, and a general bloc represented as DF-Digital.

The non-synchronous nature of data releases for the HFIs is one of the obstacles to data analysis in India. Additionally, there have been significant modifications to GVA growth figures, including limited sample sizes and data releases with significant delays. To overcome these issues, the MARSS framework applies a Kalman filter to estimate the DFs, similar to Zuur *et al*. (2003). The Kalman filter employs an Expectation Maximisation (EM) technique, which enables robust estimation for missing-value datasets and high-dimensional models with a variety of constraints (Bhadury *et al*., 2021). This strategy has been proven to be beneficial in several circumstances, see for instance, Holmes *et al*. (2014). Overall, the DFM and Kalman filter approaches used in this work offer a strong tool for evaluating complicated time series data, even in the face of missing values, data revisions, and other real-world problems.

After the construction of sectoral activity indices using a set of selected HFIs, the next step is to bridge the frequency mismatch between the monthly activity indices and quarterly GVA numbers. Several methods are available in the literature to bridge this frequency mismatch. The first method is the bridge equation method, in which we take a simple average of the monthly activity index to convert it to quarterly frequency and then put it into regression with targeted low-frequency variables which is GVA in our case as shown in Equation 4.

$$GVA_t = c + \beta_1 * GVA_{t-1} + \beta_2 * Activity\ index_t + e_t \tag{4}$$

The second method is the Almon MIDAS method, which does skip sampling of the activity index into 3 low-frequency samples for each month in a quarter. Then all the skip samples are put into an Almon Lag polynomial. The Almon polynomial is then put into the regression with the targeted low-frequency variables as shown in Equation 5.

$$GVA_t = c + \beta_1 * GVA_{t-1} + \beta_2 * b(L,\theta) Activity\ index_t + e_t \tag{5}$$

where $b(L,\theta) = \sum_{k=0}^{2} c(k,\theta)L^k$, L is the monthly lag variable, and c(k,θ) is Almon lag polynomial. The third method is the Unrestricted MIDAS(U-MIDAS) method, in which we do skip sampling of the activity index to convert them into 3 separate low-frequency samples for each month in a quarter. Then all the skip samples are directly put into the regression with the targeted low-frequency variables as shown in Equation 6.

$$GVA_t = c + \beta_1 * GVA_{t-1} + \sum_{k=0}^{2} \beta_{k+2} * L^k \, Activity\ index_t + e_t \tag{6}$$

After creating the nowcasting models using the above-mentioned methodologies, we have done their out-sample efficacy check by comparing their forecasting performance with the Naïve Bridge Equation. In the Naive Bridge Equation, we only add the previous quarter's information on the GVA growth to predict the present GVA growth as shown in Equation 7, where the GVA growth at time $\boldsymbol{t}$ is taken as the dependent variable and it is regressed on its lag. It serves as a benchmark to evaluate the efficacy of nowcasting models by comparing the increase in forecasting accuracy after the addition of the information from HFIs to the Naïve model.

$$\mathrm{GVA_t = constant + \alpha * GVA_{t-1} + e_t} \tag{7}$$

In addition, for a more realistic evaluation of the nowcasting models we have used one period ahead of sample rolling window regressions. In rolling window estimations, the in-sample model estimations are done over a sliding window of observations. The nowcasting model is first estimated over a fixed window of historical data that is used for predicting the out-of-sample GVA. Subsequently, as we move ahead to forecast GVA for the next quarter, the in-sample estimation and out-of-sample prediction windows are moved forward by one observation, and the process is repeated. Rolling regressions provide more realistic evaluations of the nowcasting models as they allow models to update themselves with incoming new information with each passing quarter. This will impact forecasting accuracy, especially in times of uncertainty and structural changes like COVID-19.

IV. EMPIRICAL FINDINGS

A. Indicators Selection

The literature on Dynamic Factor Models (DFM) presents a slew of approaches for selecting the variables used in the model. Stock and Watson (1989 and 2002) proposed the use of very large information sets, which has been adopted by many subsequent DFM papers. These large information sets are designed to capture as much information as possible, increasing the accuracy of the model's forecasts. Giannone *et al*. (2008) expanded on this concept by using over 200 economic indicators to forecast the US GDP growth. The use of such a diverse set of indicators allows the model to capture a wide range of economic activity, resulting in more accurate forecasts of economic growth. On the other hand, some literature has proposed a different approach. They proposed, starting indicators or variable selections with a relatively small set of variables known as core variables. This method aims to reduce the number of variables in the model, reducing the possibility of overfitting and increasing the interpretability of the results. Bai and

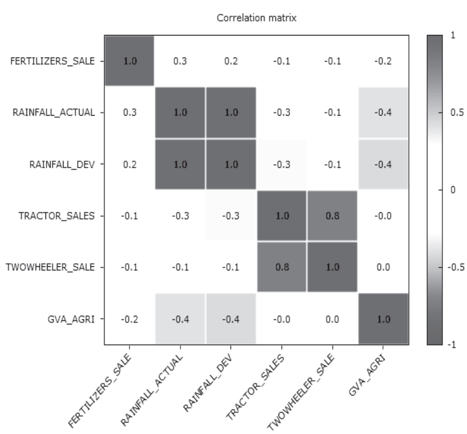
Ng (2008), Boivin and Ng (2006), and Angelini *et al*. (2011) used this method in which they started with a smaller set of core variables and then incrementally added more variables one by one based on forecast performance improvements. This method enables the researchers to assess the contribution of each additional variable to the model's predictive power and identify the variables that are most important for the model's accuracy.

Our analysis aims at investigating the relationship between high-frequency economic indicators and sectoral GVA using quarter-on-quarter seasonally adjusted annualized growth rates. We conducted a correlation analysis over a period 2017 Q1 to 2023 Q3, using around 23 observations for GVA Agriculture. We faced some constraints due to the unavailability of data for certain indicators, such as fertiliser sales before 2017. For the GVA Industry and GVA Services, we conducted a correlation analysis with associated HFIs over a period from 2013 Q1 to 2023 Q3. The correlation results are shown in Figure 1.

Figure 1.
Correlation Heatmaps

This figure presents association between Q-o-Q seasonally adjusted annualised rates (SAAR) for the period 2013 Q1 to 2022 Q3. Some of the high-frequency indicators such as electronic toll and E-way bills are only available for recent periods and hence dropped from the correlation analysis. The number of observations is 39. Most of the correlations in Figure 1(a) are found to be statistically insignificant.

a. Correlation values between high-frequency indicators related to Agriculture and GVA-Agriculture



b. Correlation values between high-frequency indicators related to industry and GVA-industry

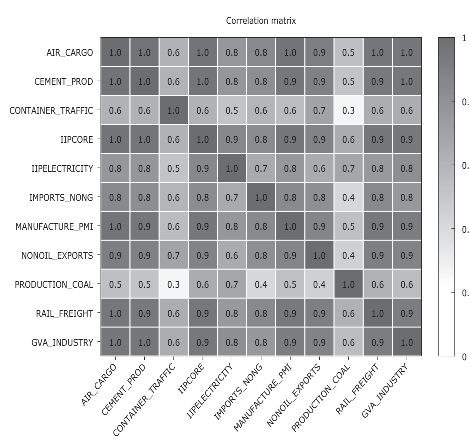
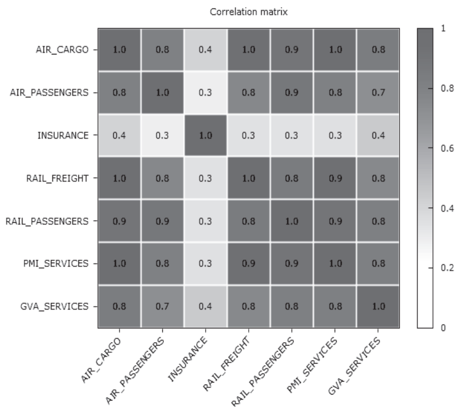
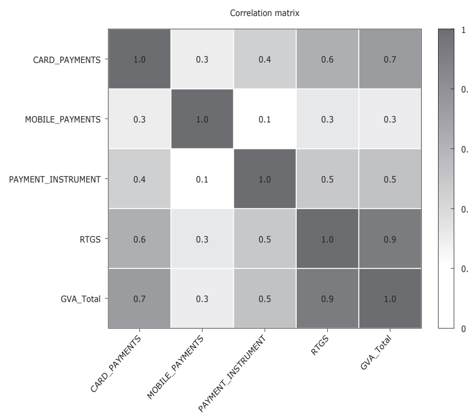


Figure 1.
Correlation Heatmaps (Continued)

c. Correlation values between high-frequency indicators and GVA-Services



d. Correlation values between digital high-frequency indicators and GVA-Total.



Source: Authors' calculation.

In addition, the rapid digitalisation of various sectors of the economy in recent years has motivated us to introduce a digital bloc in our nowcasting model, comprising various high-frequency indicators such as card payments, mobile payments, payment instruments, RTGS, electronic tolls, E-way bills, NPCI retail payment, and other digital platforms. Including these indicators in nowcasting India's GVA data is important as it provides a more accurate and timely assessment of the country's economic activity. With the increasing reliance on digital platforms for conducting transactions, tracking digital indicators can help capture real-time changes in economic activity and provide valuable insights into the state of the economy. Additionally, it enables policymakers to make more informed decisions and implement effective measures to support economic growth and development. Accordingly, we conduct a correlation analysis between aggregate GVA and high-frequency indicators representing digital transactions over a period 2013 Q1 to 2022 Q3. The result of the correlation analysis between the momentum of digital indicators and total GVA is shown in Figure 10

We look at the association between the variable of interest and high-frequency indicators in the recent period, keeping in mind that many HFIs may have become less relevant in the last decade. To determine the nature of dependence among variables, we employed the widely accepted cross-correlation test. This test established the significance of cross-correlation at various lags and indicated the nature of dependence based on the sign of correlation. Variables with significant cross-correlation at lag = 0 and appropriate signs were included in the first pool of variables. However, we acknowledge that high cross-correlation alone does not account for the switching of processes, a critical property of any business cycle indicator as identified by Burns and Mitchell (1946).

We observe a few interesting results regarding the relationship between various HFI and GVA in the three major sectors of the economy. None of the HFIs, such as fertiliser sales, two-wheeler sales, rainfall actual or deviation, and tractor sales, exhibited a strong contemporaneous association with GVA in the agriculture sector. However, HFIs such as air cargo, cement production, PMI manufacturing, non-oil exports, and rail freight were found to exhibit a strong association with GVA in the industry sector. Similarly, rail freight, rail passenger, PMI services, and air cargo are found to have a strong association with GVA in the services sector. For the digital bloc, RTGS, card payment, etc. are observed to have a strong, positive association with aggregate GVA. These results indicate that different HFIs correlate well with the different sectors of the economy and can be useful in nowcasting economic performance.

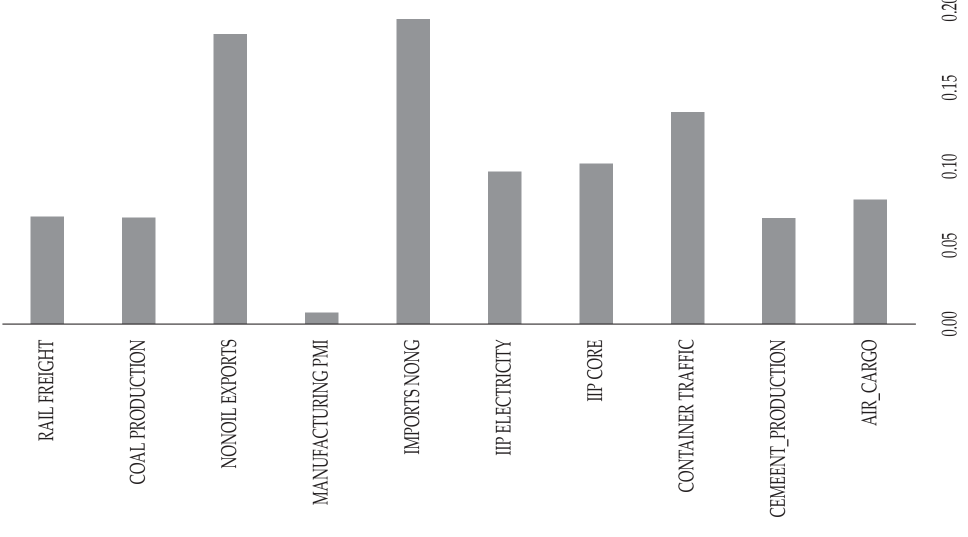
B. Dynamics in the Dynamic Factors (DFs): Past and Present

B.I. DF: Industry

We explore the dynamics of the DF for the industrial bloc (referred to henceforth as DF: Industry) in both the pre- and post-COVID-19 periods. The *DF: Industry* represents the common trend in monthly high-frequency indicators such as rail freight, coal production, non-oil exports, PMI manufacturing, non-oil and non-gold imports, IIP electricity, IIP core, container traffic, cement production, and air cargo (Figure 2).[8]

Figure 2.
Factor Loadings (Industry)

This figure shows the factor loadings of HFIs in the Industry Activity Index Source: Authors' calculation.



8 Multicollinearity arises when input variables exhibit strong correlations with one another within a dataset. This can often impede the performance of regression and classification models. To address this issue, dimension reduction techniques like principal component analysis (PCA) and dynamic factor model (DFM) can be employed. These techniques leverage the presence of multicollinearity by amalgamating highly correlated variables into a set of uncorrelated variables. Consequently, they effectively alleviate the multicollinearity concern among features. In our specific scenario, the GVA industry bloc incorporates indicators such as cement, electricity, coal production, and IIP Core. The DFM aims to extract an underlying, consensus trend from these indicators that collectively exhibit co-movement.

We highlight that the monthly indicators are highly volatile in an emerging economy like India. Despite removing their idiosyncratic components, their volatility creeps into the estimated trend, making it challenging to identify the true underlying dynamics of the DF: Industry. To overcome this challenge, we use a year-on-year variation in the DF: Industry, which is depicted in the figure 3 . This approach captures the overall trend in the data, thereby allowing for a better understanding of the underlying dynamics of the DF industry. We observe that the dynamics in DF capture the COVID-19 lockdown period where economic activity crashed, followed by a pent-up demand-led recovery of economic activity. This finding is significant, as it highlights the extent of the impact of the COVID-19 pandemic on the Indian economy, particularly in the industrial sector (Figure 3).

Moreover, we note that the dynamics in the *DF: Industry* also capture the GFC crisis. This observation suggests that the *DF: Industry* is a robust indicator of the Indian economy's performance, as it captures the impact of major economic disruptions. Thus, we argue that the use of HFIs is essential to capture the underlying dynamics of industrial activity in emerging economies like India.

Figure 3.
Pre-pandemic and Post-pandemic Industry Movements

This figure reports the dynamics of the DF for the industrial bloc (referred to henceforth as DF: Industry) in both the pre- and post-COVID-19 periods. The associated factor loadings are represented in the left panel.

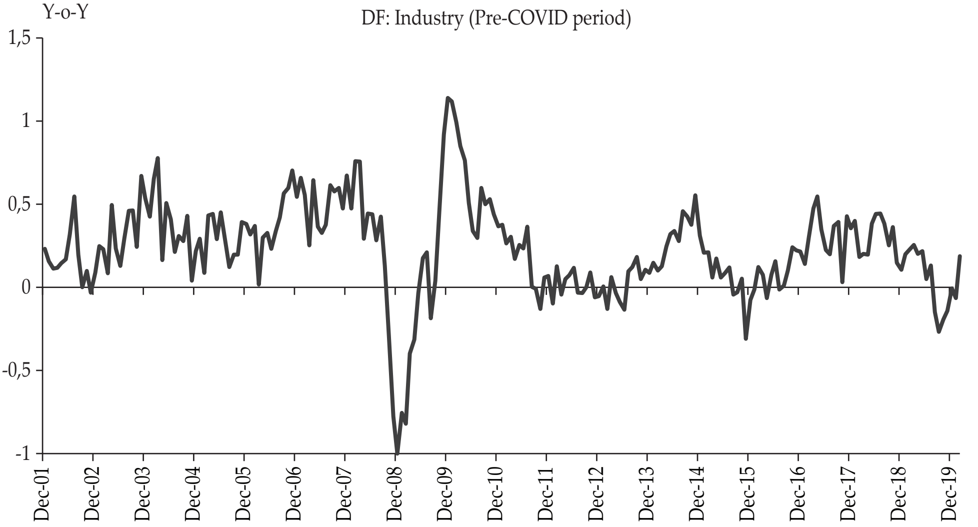
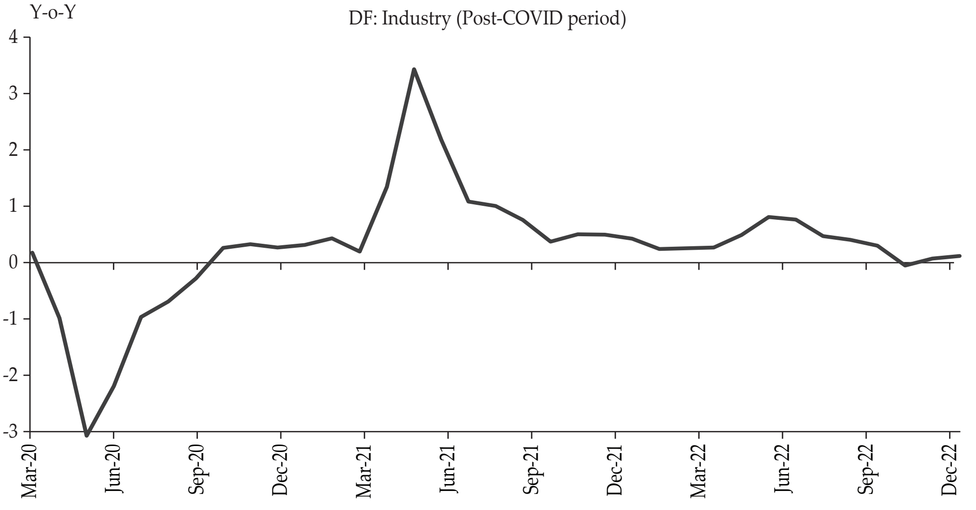


Figure 3.
Pre-pandemic and Post-pandemic Industry Movements (Continued)



Source: Authors' calculation.

B. II. DF: Services

Next, we explore the dynamics of the DF for services bloc (referred to henceforth as *DF: Services*) in both the pre-and post-COVID-19 periods. Separately tracking industrial and service activity using HFIs is important for nowcasting GDP in India for several reasons. Firstly, the two sectors have different patterns of growth and volatility and hence may respond differently to economic shocks (shown in detail in the next subsection). Secondly, the composition of GDP in India has shifted over time, with the services sector accounting for a larger share of the economy. Therefore, tracking the performance of the services sector separately becomes crucial to accurately estimating GDP.

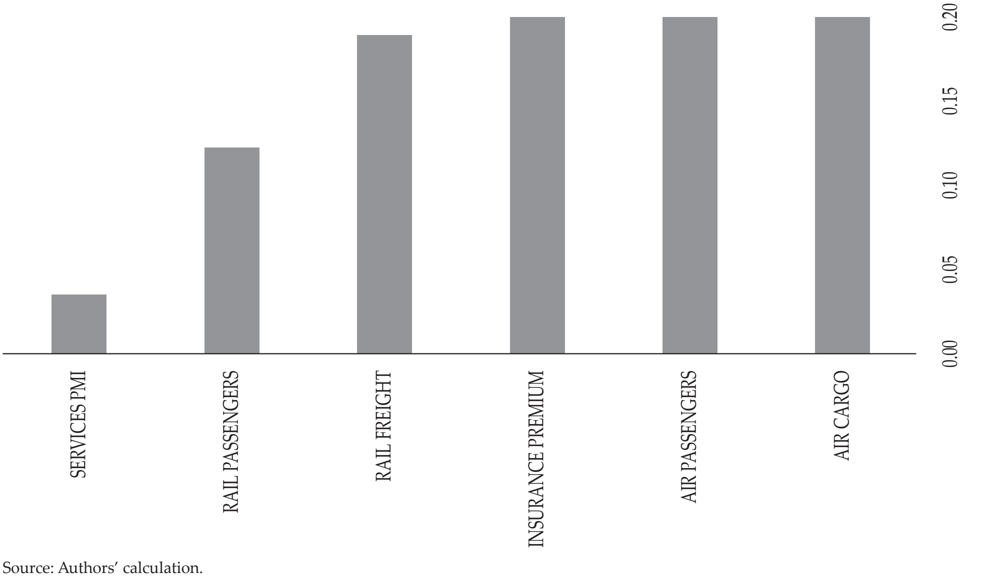
Taking cue from the paper, Roy *et al*. (2018), our study has drawn upon a larger set of approximately 12 HFIs traditionally employed to gauge activity within the services sector. However, it is important to recognize that nowcasting models designed for policy-making purposes are intended to address two primary challenges: the risk of overfitting and maintaining tractability. In cognizance of these dual concerns, our analysis has undertaken the estimation of services sector activity utilizing a refined set of 6 HFIs that exhibit a strong association with GVA in the services sector. This streamlined approach not only aligns with the overarching goal of ensuring model tractability but also effectively addresses the prevalent issue of overfitting. The challenge of overfitting is often characterized by models performing exceptionally well within the sample data, only to perform poorly when applied to data outside the sample. By employing a limited number of HFIs and strategically prioritising the most relevant ones, we effectively manage the risk of overfitting.

In this regard, the DF: Services represents the common trend in monthly HFIs related to the services sector, such as PMI services, rail passengers, air passengers, rail freight, insurance premium, air passengers, and air cargo (Figure 4 and Figure

5).Similar to DF Industry, the DF services seem to be a robust indicator for the performance of the services sector, as it can capture the impact of the economic shocks the COVID-19, GFC, etc.

Figure 4.
Factor Loading (services)

This figure shows the factor loadings of HFIs in Services Activity Index.



Source: Authors' calculation.

Figure 5.
Pre-pandemic and Post-pandemic Dynamic Factor (Services) Movement

This figure reports the dynamics of the DF for the services bloc (referred to henceforth as DF: Services) in both the pre-and post-COVID-19 periods. The associated factor loadings are represented in the left panel.

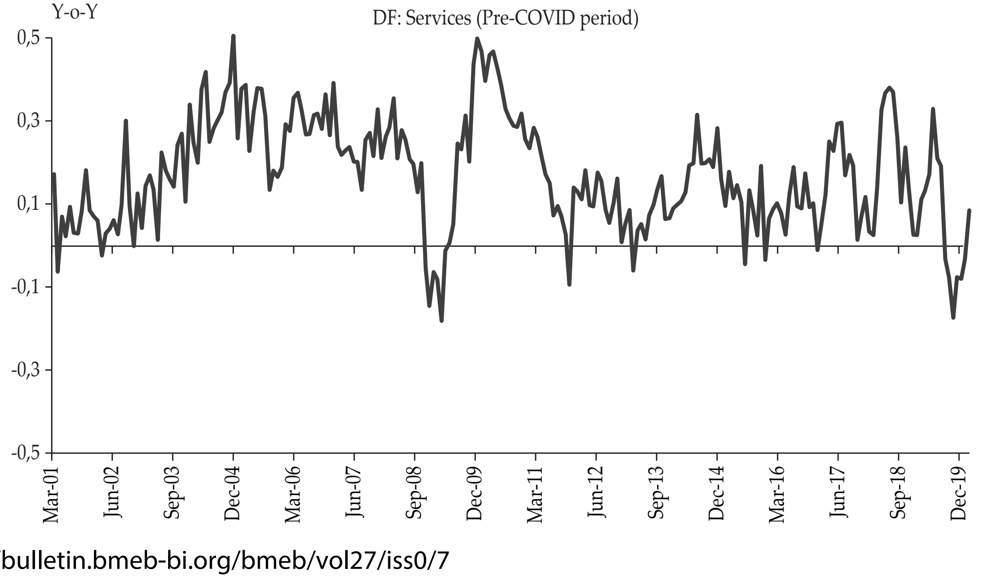
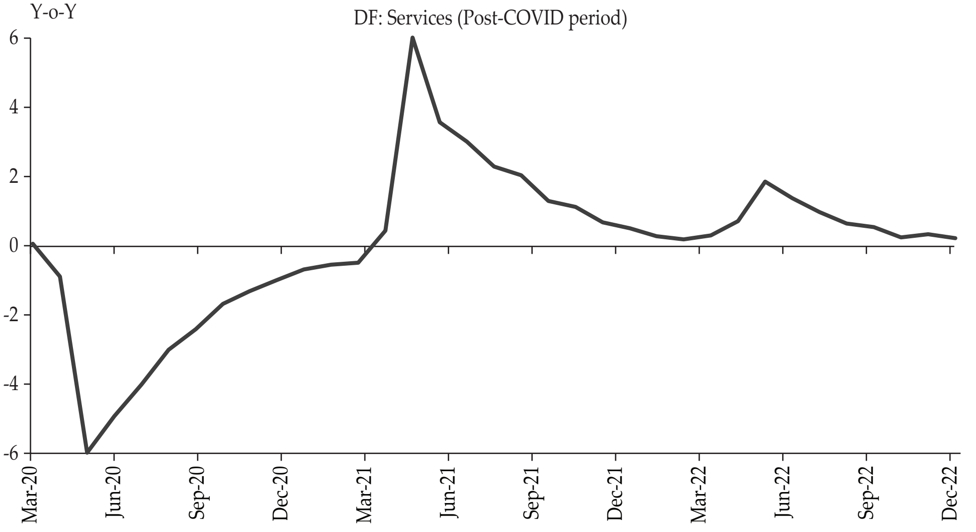


Figure 5.
Pre-pandemic and Post-pandemic Dynamic Factor (Services) Movement (Continued)



Source: Authors' calculation.

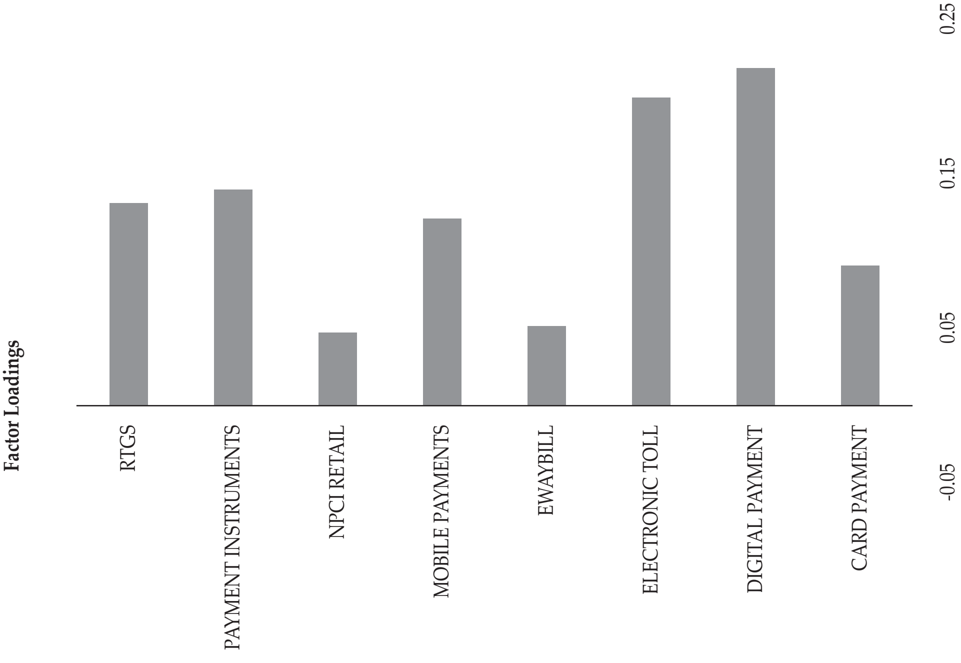
B.III. DF: Digital Economy

As discussed earlier, the Digital economy has been rapidly growing in India and is expected to have a significant impact on the overall GDP. The digital economy includes various activities such as e-commerce, digital payments, software development, and Information Technology-Enabled Services (ITES). These activities are typically not captured by traditional measures of economic activity, and therefore, a separate digital sector is necessary to account for their contribution to GDP. By tracking the digital economy separately, policymakers and investors can gain a more accurate and timely understanding of the overall economic activity in India. This is particularly important given the fast-paced nature of the digital economy, where new products and services are introduced at a rapid pace and traditional measures of economic activity may not capture them adequately.

Therefore, we explore the dynamics of the DF for the digital bloc (referred to henceforth as DF: Digital) in both the pre- and post-COVID-19 periods. Monthly HFIs such as RTGS, payment instruments, NPCI retail payments, mobile payments, Eway bills, electronic toll, and card payments represent the common trend in DF: Digital (Figures 6 and 7).

Figure 6.
Factor Loading (Digital Block)

This figure shows the factor loading of HFIs in Digital Index.



Source: Authors' calculation.

Figure 7.
Pre-pandemic and post-pandemic Digital Block Movement

This figure reports the dynamics of the DF for the digital bloc (referred to henceforth as DF: Digital) in both the pre- and post-COVID-19 periods. The associated factor loadings are represented in the left panel.

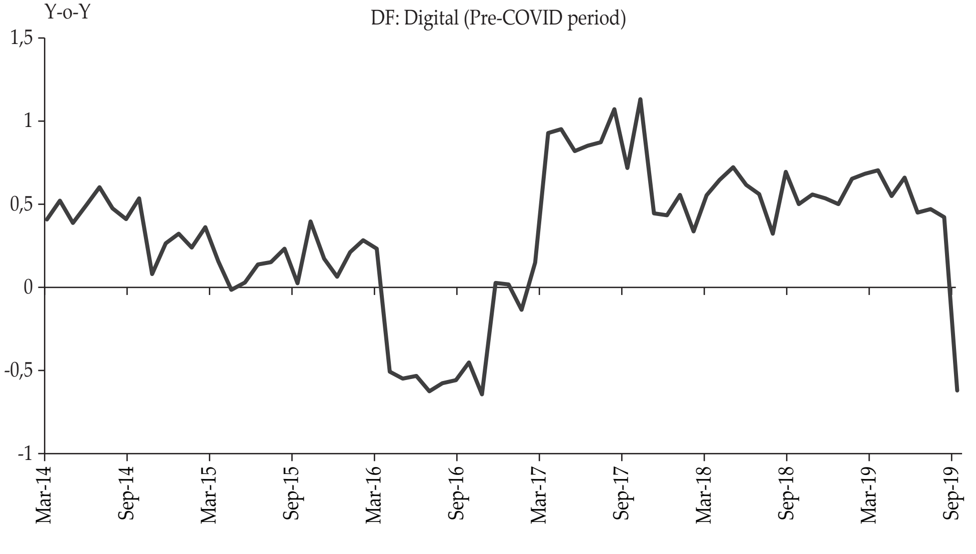
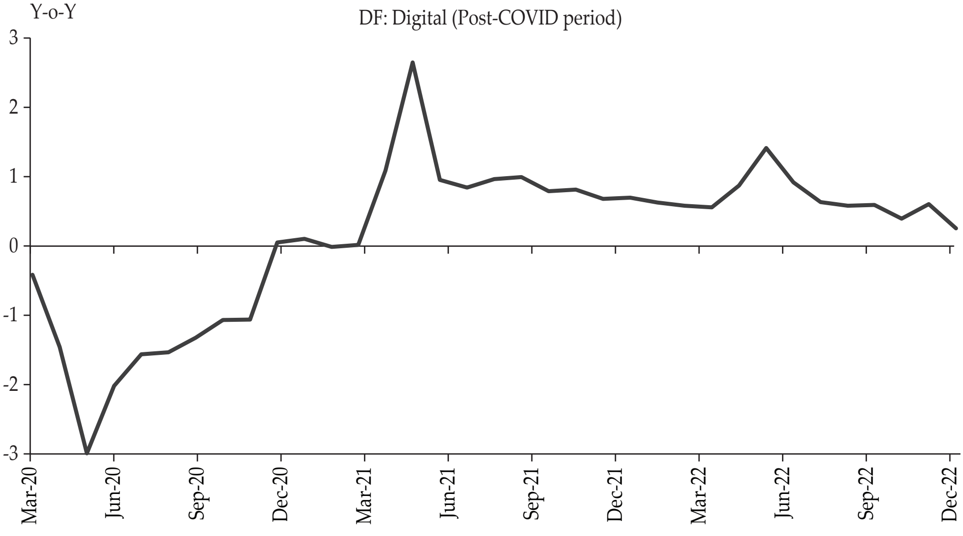


Figure 7.
Pre-pandemic and post-pandemic Digital Block Movement (Continued)



Source: Authors' calculation.

Figure 7 shows that in the pre-pandemic period, the digital index is more stable at a higher level compared to the Industry DF and Services DF, indicating the increasing digitisation of the economy in that period. However, in the post-pandemic period, the movement in the digital index captures the movement of the economy well, as the negative growth in the economy and subsequent recovery during the pandemic, are also captured in the movement of the DF Digital. Thus, the digital index can help gauge the movement in the economy in times of uncertainty and structural changes, as in the post-COVID-19 period.[9]

C. Sectoral Heterogeneity of Economic Shocks

As discussed earlier, the impact of economic shocks such as the COVID-19 pandemic and subsequent recovery has exhibited heterogeneity across sectors, highlighting the need for a more granular approach in nowcasting GVA by separately considering agriculture, industry, and services. In this subsection, we provide further empirical evidence to support this argument.

The sectoral heterogeneity becomes evident when observing Figure 8, which depicts the growth of agricultural GVA compared to that of the industry and services sectors during the COVID-19 shock. Agricultural GVA growth remained largely unaffected, while the industry and services sectors experienced more pronounced effects. Furthermore, the recovery from the COVID-19 shock exhibited heterogeneity, with the industrial sector largely recovering in the following year, whereas the services sector took two years to recover due to the impact

[9] Time periods for model evaluation: pre-pandemic – 2019 Q1 to 2020 Q1, post-pandemic – 2021 Q3 to 2022 Q3.

of subsequent waves, such as the delta variant and its dependence on contact-sensitive sectors. Additionally, the sectoral heterogeneity in year-on-year (Y-o-Y) growth has considerably increased during and after the pandemic compared to the pre-pandemic period.

Similarly, Figure 8 also illustrates the heterogeneous impact of other economic shocks, such as the Global Financial Crisis (GFC), on different sectors. GFC had a more severe impact on the industry sector compared to the services sector. On the other hand, agricultural GVA growth seems to be less influenced by economic shocks like the GFC and COVID-19, as it is more dependent on factors such as rainfall and temperature. Thus, evaluating nowcast models in both pre-pandemic and post-pandemic periods is necessary at the sectoral level.

This empirical evidence further supports the argument for a granular approach in nowcasting GVA, considering the heterogeneity of sectoral impacts during economic shocks and recoveries. By separately analyzing agriculture, industry, and services, a more accurate understanding of sector-specific dynamics can be achieved, allowing for improved nowcasting at the sectoral level.

Figure 8.
Sectoral GVA Growth Around Crises Periods

This figure shows the heterogenous impact of economic shocks on different sectors. The left panel shows the YoY growth of Agriculture GVA, Services GVA and Industry GVA at quarterly frequency during COVID period while right panel shows the YoY growth of Agriculture GVA, Services GVA and Industry GVA at quarterly frequency during COVID period while right panel.

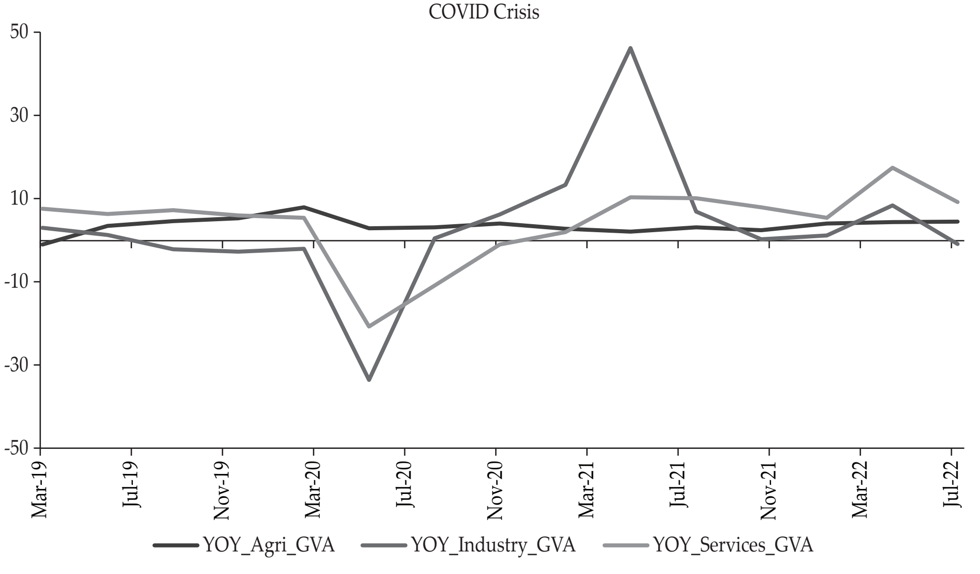
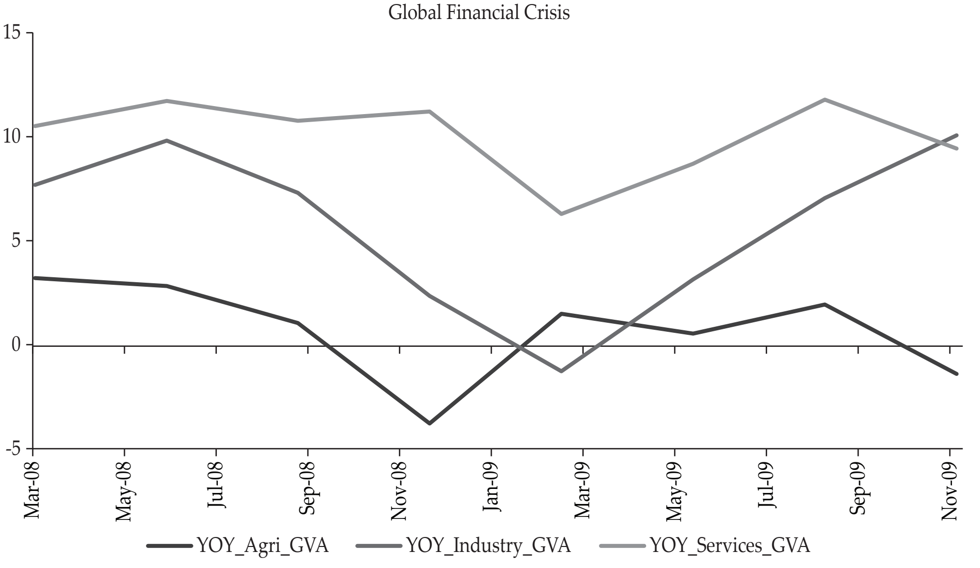


Figure 8.
Sectoral GVA Growth Around Crises Periods (Continued)



Source: Ministry of Statistics and Program Implementation, NSO

D. Bridge Equations Estimation

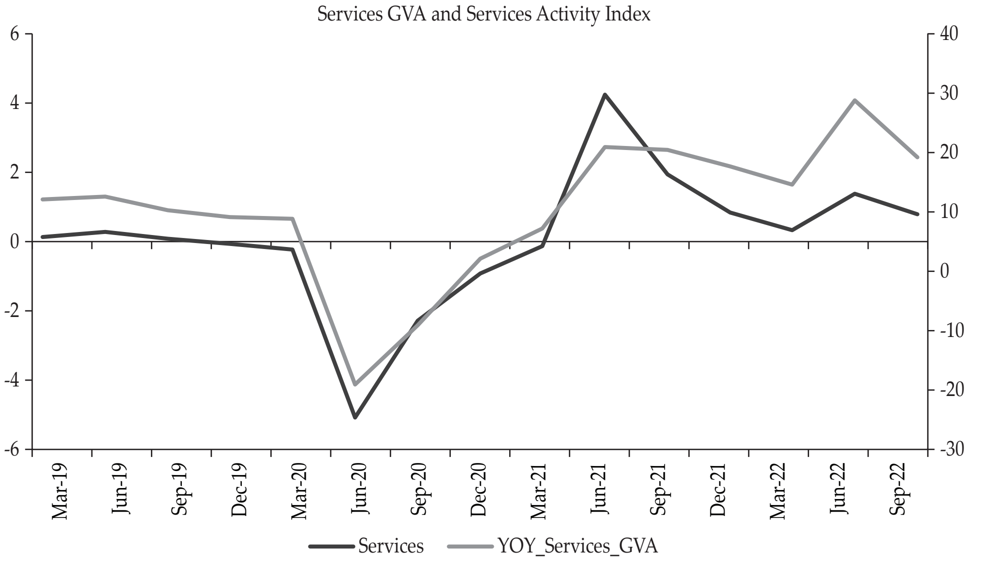
In this section, we have conducted separate bridge equations for Agriculture, Services, and Industry to analyse the year-on-year (Y-o-Y) GVA growth. These equations include lagged variables, Activity Indices, and a dummy variable called "Covid" to represent the period starting from the onset of the COVID-19 pandemic, as shown in equation 8:

$$GVA_t = constant + \alpha * GVA_{t-1} + \beta * DF_t + \gamma * Covid + e_t \tag{8}$$

To interpret the results of the bridge equation estimations, we examine Figure 9, which presents time series plots of growth of Industry GVA, Services GVA, and Agriculture GVA along with their respective activity indices during the pandemic period. From the plots, we observe that the activity indices of industry and services closely track the movements of their respective GVA, similar to tracking of the GDP movement by economic activity index in Bhadury *et al*. (2021) in which the economic activity index constructed from HFIs using dynamic factors was tracking the GDP growth well. However, the activity index of agriculture does not show a strong correlation with the movement of Agriculture GVA. Therefore, we have also included the growth of rainfall, which is observed to have a stronger correlation with growth in Agriculture GVA (Figure 9). This indicates that rainfall growth with a lag might be correlated with Agriculture GVA growth.

Figure 9.
Movement of Sectoral Activity Indices with Sectoral GVAs in Post Pandemic Period

This figure indicates the movements of various activity indices along with their corresponding sectoral GVA growth. The upper left chart shows the movement of Services Activity Index along with movement of YoY growth of Services GVA. The upper right chart shows the movement of Industry Activity Index along with movement of YoY growth of Industry GVA. The lower left chart shows the movement of Agriculture Activity Index along with movement of YoY growth of Agriculture GVA. The lower right chart shows the movement of Rainfall Deviation from long term average along with movement of YoY growth of Agriculture GVA.



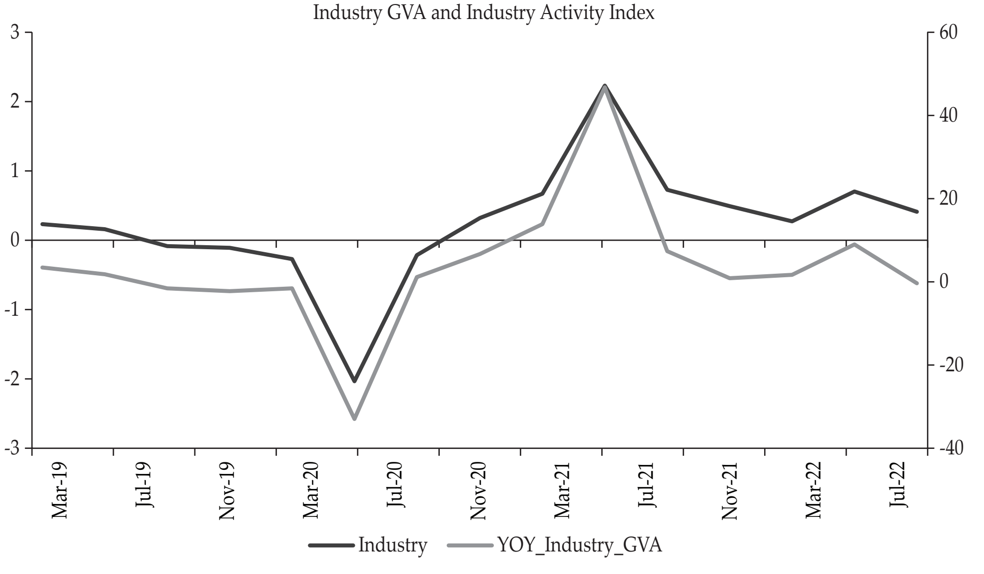
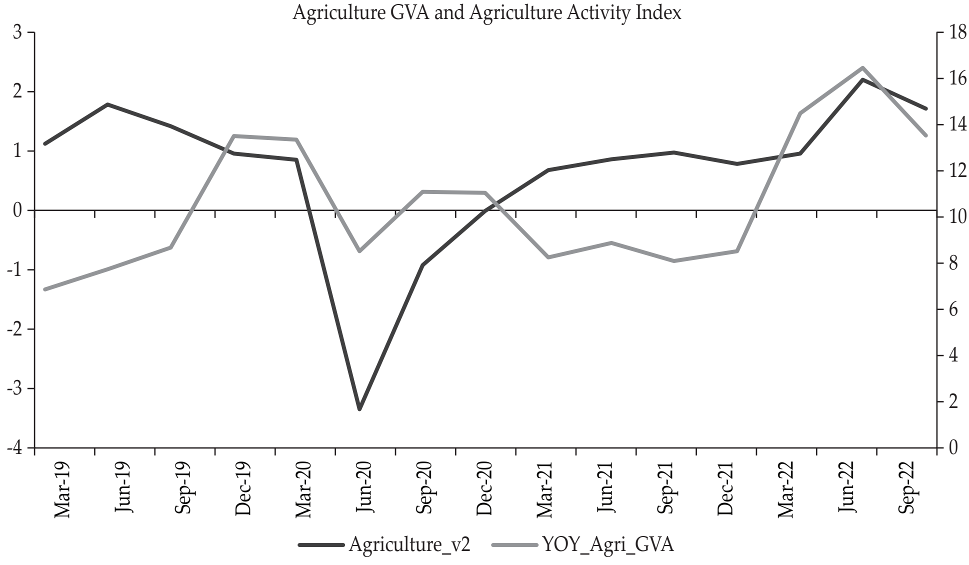
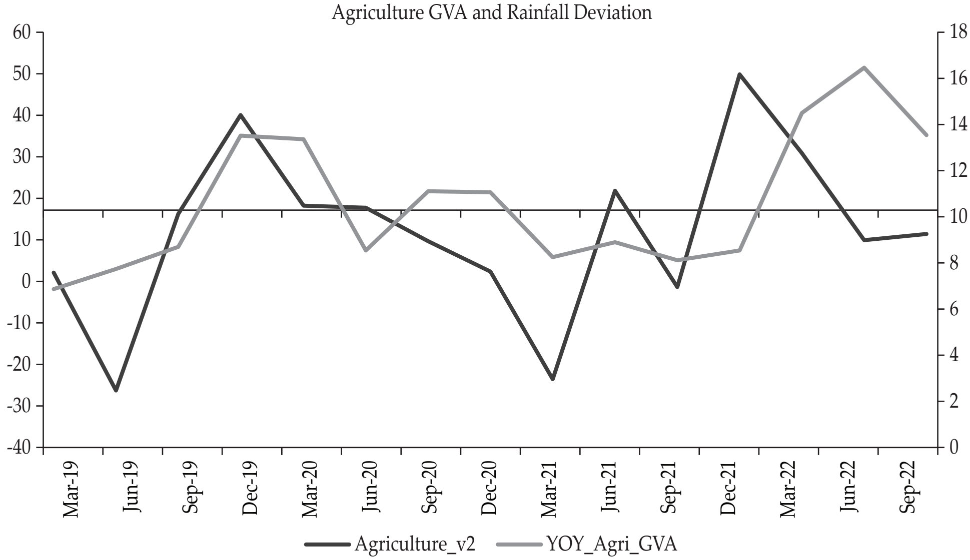


Figure 9.
Movement of Sectoral Activity Indices with Sectoral GVAs in Post Pandemic Period (Continued)





Source: Authors' calculation.

Table 3.
Bridge Equations Estimation Results

This table presents the results of Bridge equation estimations of various bridge models used in the study to nowcast sectoral GVAs. Part A of table shows the bridge estimations in nowcasting sectoral GVAs using Digital Index. Part B shows the bridge estimations in nowcasting sectoral GVAs using their corresponding sectoral activity indices. Part C shows the bridge estimations in nowcasting sectoral GVAs using their corresponding sectoral activity indices and GSCDCI. Part D shows the bridge estimations in nowcasting sectoral GVAs using their corresponding sectoral activity indices and Digital Index. Part E shows the bridge estimations in nowcasting sectoral GVAs using their corresponding sectoral activity indices, Digital Index and GSCDCI.

Time Period – 2012Q1 – 2022Q2. *** denotes 1% significance level, ** denotes 5% significance level, and *denotes 10% significance level.

Part A: Bridge Equation Estimations with Digital Index

Variables	**Services**		**Industry**		**Agriculture**	
	Coeff.	***P*-value**	**Coeff.**	***P*-value**	**Coeff.**	***P*-value**
Digital Index	3.20***	0	5.48**	0	0.50***	0
Lag of Sectoral GVA Growth	0.47***	0	0.15	0.29	-0.47	0.3
Constant	2.30**	0.02	0.27	0.12	1.88***	0
Adjusted R^2	0.51		0.22		0.38	

Part B: Bridge Equations Estimation Results with Sectoral Activity Indices

Variables	**Services**		**Industry**		**Agriculture**		**Agriculture with Rainfall Growth**	
	Coeff.	***P*-value**	**Coeff.**	***P*-value**	**Coeff.**	***P*-value**	**Coeff.**	**P-value**
Sectoral DF	4.41***	0	15.24***	0	0.09	0.77		
Lag of Sectoral GVA Growth	0.19**	0.01	0.17	0.78	0.49**	0	0.49***	0
Lag of Rainfall Growth					0.01	0.1	0.01	0.11
Covid	-3.41***	0	-2.90**	0.03	-0.53	0.59		
Constant	6.11***	0	3.38***	0	1.74***	0	1.78***	0
Adjusted R^2	0.73		0.74		0.2		0.23	

Part C: Bridge Equation Estimation Results with Sectoral Activity Indices and GSCDCI

Variables	**Services**		**Industry**		**Agriculture with Rainfall Growth**	
	Coeff.	***P*-value**	**Coeff.**	***P*-value**	**Coeff.**	***P*-value**
Sectoral DF	4.11***	0	15.3***	0		
Lag of Sectoral GVA Growth	0.28***	0	0.05	0.44	0.48***	0
Lag of Rainfall Growth					0.01	0.11
GSDCI	0.01	0.38	-0.04	0.16	0.02***	0
Constant	3.01	0.19	7.6**	0.02	0	0.99
Adjusted R^2	0.67		0.71		0.21	

Table 3.
Bridge Equations Estimation Results (Continued)

Part D: Bridge Equations Estimation Results with Digital Index and Sectoral Activity Indices

Variables	Services		Industry		Agriculture	
	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Sectoral DF	3.94***	0	19.07***	0	1.7***	0
Digital Index	-0.58	0.48	-2.06*	0.07	-1.57**	0.01
Lag of Sectoral GVA Growth	0.23**	0.01	-0.04	0.6	0.60***	0
Covid	-3.51**	0.01	-4.27**	0.01	0.52	0.47
Constant	5.78	0	4.04	0	0.52	0.47
Adjusted R^2	0.79		0.81		0.4	

Part E: Bridge Equation Estimation Results with Digital Index, Sectoral Activity Indices and GSCDCI

Variables	Services		Industry		Agriculture	
	Coeff.	*P*-value	Coeff.	*P*-value	Coeff.	*P*-value
Sectoral DF	4.0***	0	18.88***	0	1.68***	0
GSCDCI	0.01*	0.06	-0.16**	0.03	0.01	0.63
Digital Index	-1.64*	0.09	-2.36	0.19	-1.75***	0
Lag of Sectoral GVA Growth	0.18*	0.05	-0.04	0.56	0.60***	0
Covid	-4.97***	0	-2.36	0.19	0.11	0.9
Constant	-4.77	0.4	21.99***	0	0.11	0.72
Adjusted R^2	0.8		0.75		0.39	

Panel B of Table 3 provides a summary of the regression results obtained by estimating Equation 5 for agriculture, industry, and services GVA. The results align with the findings from Figure 9, where the coefficients of the industry and services activity indices are statistically significant at a 5 per cent level, indicating their explanatory power in accounting for the variations in their respective sectoral growth. However, the coefficient of the agriculture activity index is found to be statistically insignificant, suggesting that the agriculture sector's activity index lacks explanatory power in explaining the growth of Agriculture GVA. The COVID dummy variable is negative and statistically significant for industry and services GVA, implying a decrease in growth of GVA after the onset of COVID-19, considering a given level of activity index. However, the COVID dummy is statistically insignificant for Agriculture GVA, indicating that COVID-19 do not have a significant impact on the growth of Agriculture GVA. Furthermore, we conducted a regression with Agriculture GVA as the dependent variable and included lagged variables of rainfall growth and Agriculture GVA as explanatory variables. In this regression, the lagged variable of rainfall growth shows a *p*-value close to a 10 per cent significance level, indicating its potential usefulness in nowcasting the Agriculture GVA.

The empirical findings of this section indicate that the pandemic indeed had heterogeneous impacts on different sectors, wherein the services sector withstood the maximum brunt, while the agricultural sector perhaps experienced the least. This could be the primary reason behind the errors in the post-pandemic nowcasting exercises, which solely depended on macro-aggregates rather than granular sectoral datasets. Moreover, indicators like digital finance, which assumed importance since the pandemic, may increase in importance. In the following section, therefore, we are examining the potential use of digital transaction data in nowcasting the GVA of Agriculture, Industry, and Services.

E. Inclusion of Digital Index in the Nowcasting Sectoral GVA.

Considering the increasing digitization and formalization of the economy, particularly accelerated by the COVID-19 pandemic, it becomes highly valuable to explore digital financial and payment transaction data for assessing current economic activity.

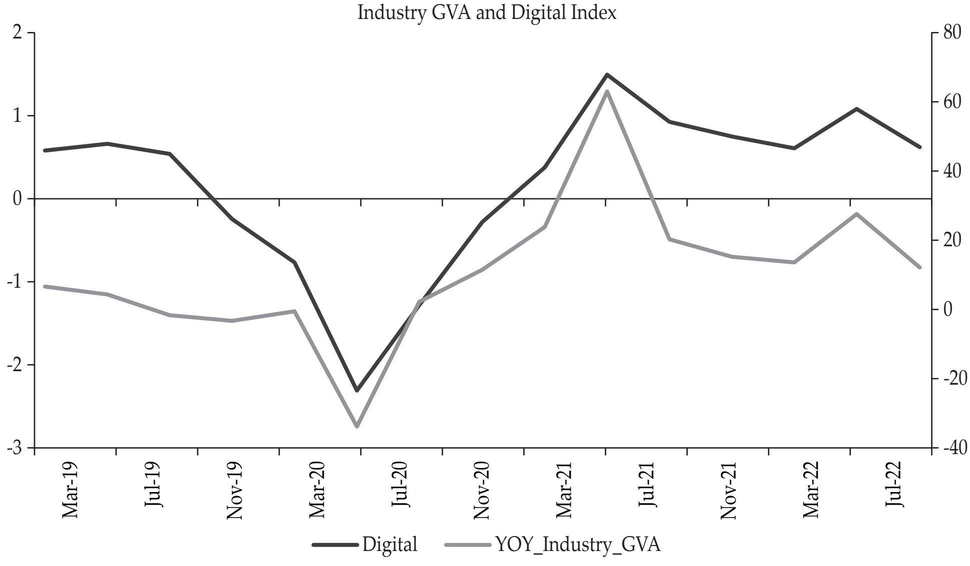
First, we selected various available digital transaction data sources such as card payments, mobile payments, electronic toll payments, RTGS transactions, E-way bills, etc. They were then combined using DFA to create a composite index known as the digital index. Then, we have analysed movement of the digital index with the growth of Services, Industry, Agriculture, and Aggregate GVA. Figure 10 illustrates the correlation between the digital index and the growth of these sectors. We observe that the growth of Services, Industry, and Aggregate GVA closely aligns with the movement of the digital index. However, for Agriculture GVA growth, the digital index does not exhibit a similar correlation. Subsequently, we incorporate the digital index into the bridge equation as shown in Equation (9):

$$GVA_t = constant + \alpha * GVA_{t-1} + \beta * Digital\ Index_t + \gamma * Covid + e_t \quad (9)$$

The regression results are summarized in Panel A of Table 3., these results indicate that the digital index explains the variation in Services GVA to the greatest extent, followed by Industry GVA, but it does not significantly explain the variations in Agriculture GVA. However, the regression results summarized in Table 3 Panel D, in which we took digital index in the models along with sectoral activity indices show that performance of the digital index in presence of sectoral activity indices (Industry and Services) is mixed due to possible multicollinearity between the sectoral activity indices (Industry and Services) and the digital index. The performance of agriculture activity index improved considerably after inclusion of digital index in the model. However, this could be a statistical anomaly, as Panels A and B of Table 2 show that individually agriculture activity index and digital index do not significantly explain the variations of Agriculture GVA growth.

Figure 10.
Movement of Digital Index with Sectoral GVA

This figure shows the movement of Digital Index with movement of various sectoral GVA YoY growth. The upper left chart shows the movement of Digital Index along with movement in YoY growth in Industry GVA. The upper right chart shows the movement of Digital Index along with movement in YoY growth in Services GVA. The lower left chart shows the movement of Digital Index along with movement in YoY growth in Agriculture GVA. The lower right chart shows the movement of Digital Index along with movement in YoY growth in the total GVA of Indian economy.



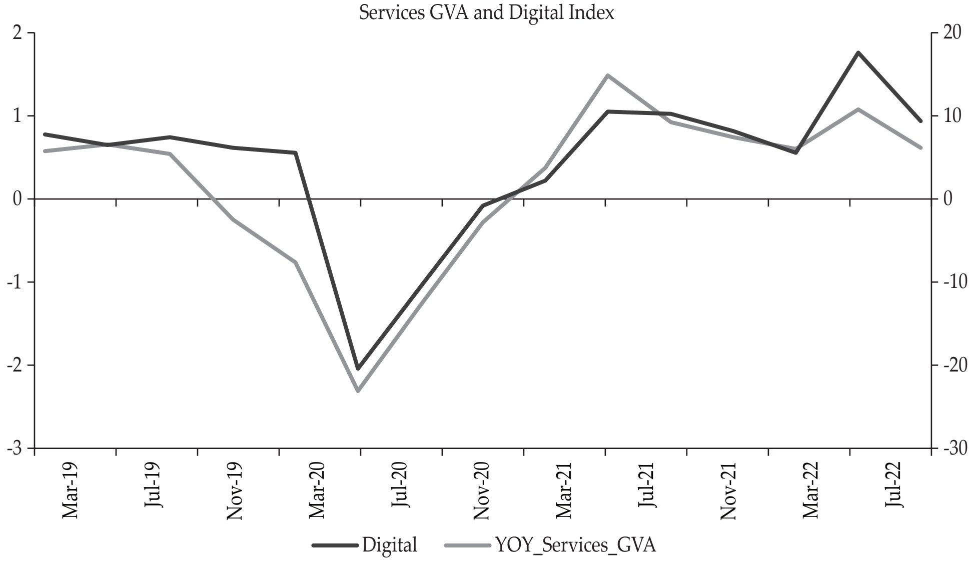
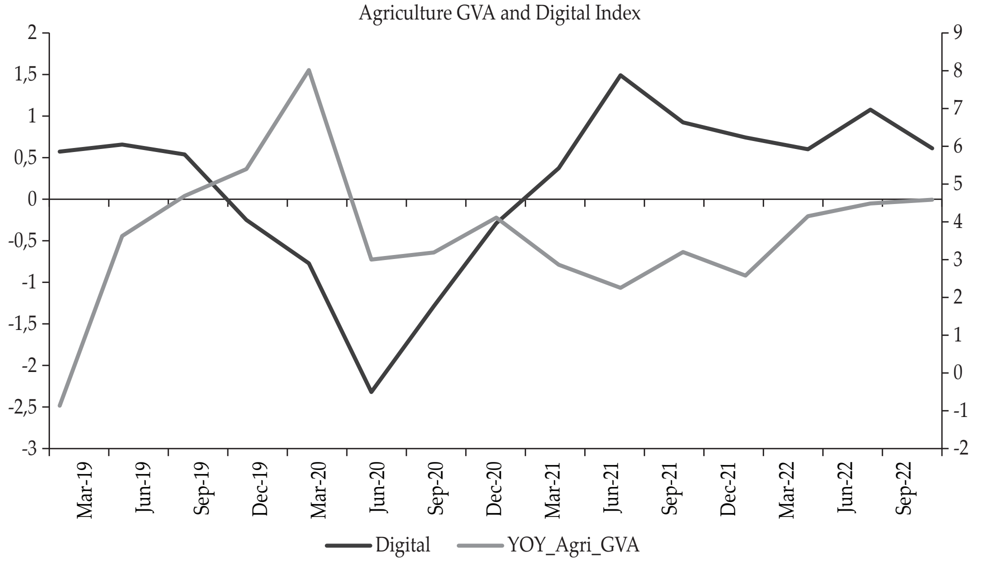
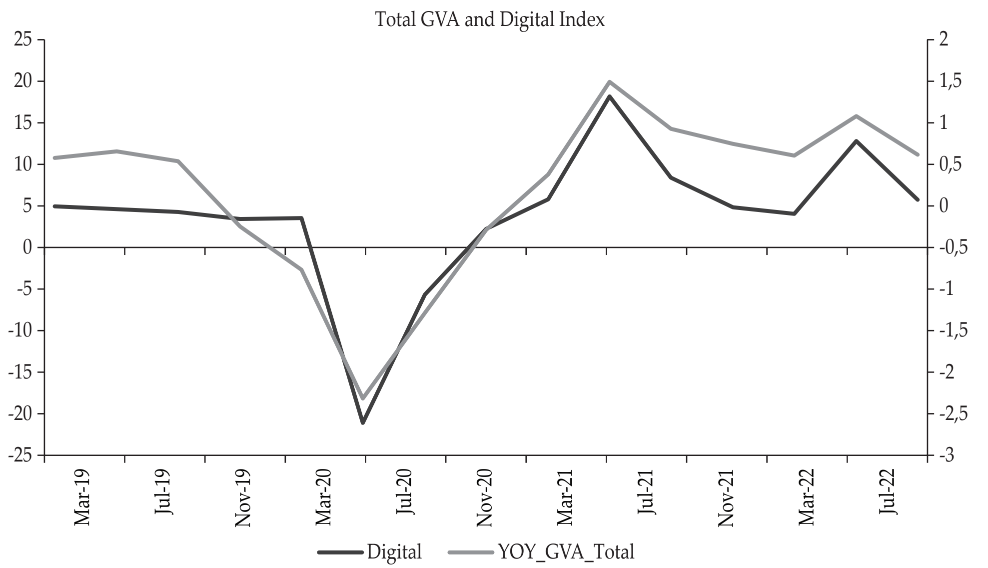


Figure 10.
Movement of Digital Index with Sectoral GVA (Continued)





Source: Authors' calculation

F. Inclusion of Global Supply Chain Disruption Index (GSDCI)

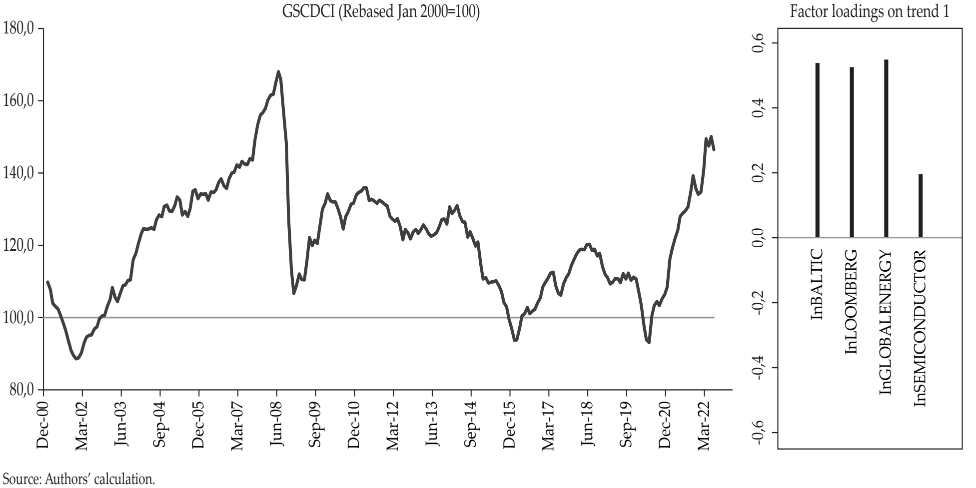
The COVID-19 pandemic and other factors have introduced significant risks to the Indian economy through global supply chain disruptions. In this paper, we aim to investigate whether incorporating these disruptions into the nowcasting models improves the accuracy of forecasting the Indian economy's GVA. To achieve this, we introduce a novel index, the Global Supply Chain Disruption Cost Index

(GSCDCI), which captures the costs associated with such disruptions.[10] GSCDCI is rooted in the assumption of a small open economy, with India considered as a price-taker. In the context of India, which heavily relies on imports of oil and commodities, the index incorporates factors such as energy and commodity prices and freight rates, which encompass shipping costs. Furthermore, recognizing the growing influence of the semiconductor market on global supply chains and India's aspiration to play a significant role therein, we have included semiconductor billing in the index.

The GSCDCI is constructed using a dynamic factor model that extracts a common factor from four monthly indicators: the Baltic Dry Index, Bloomberg Commodity Index, IMF Fuel (Energy) Index, and Semiconductor Equipment Billing. These indicators reflect changes in demand and supply conditions for various commodities and intermediate goods that are crucial for production and investment activities. Figure 11 illustrates the movement of the GSCDCI from the year 2000 onwards along with associated factor loadings. A higher value of the GSCDCI signifies greater costs attributed to supply chain disruptions, lower prospects for investment and weaker growth outlook. A varimax rotation[11] scheme is used to determine the factor loads of Baltic Dry Index, Bloomberg Commodity Index, IMF Fuel (Energy) Index, and Semiconductor Equipment Billing on trend 1, which is the common factor that we are interested in.

Figure 11.
Plot of Global Supply Chain Disruption Cost Index (GSCDCI)

This figure shows the movement of GSCDCI along with factor loadings of HFIs in constructing GSCDCI. The right chart shows the factor loadings of the HFIs, and the left chart shows the movement of GSCDCI from December 2000.



Source: Authors' calculation.

[10] The Global Supply Chain Disruption Index is a measure obtained by extracting the dynamic factor from several key indicators. This index serves as a quantitative assessment of the extent of disruptions experienced in the global supply chain. As part of our analysis, we conducted a robustness check using the global supply chain pressure index. However, contrary to our expectations, the inclusion of the pressure index did not result in an improvement in the model fit.

[11] The Varimax scheme seeks a rotation matrix that creates the largest possible difference between loadings.

We employ this index to estimate the impact of global supply chain disruptions on India's sectoral GVA growth using a bridge equation model, represented by Equation (10). The regression results are summarized in Panel C of Table 3.

$$GVA_t = constant + \alpha * GVA_{t-1} + \beta * GSCDCI_t + \gamma * \ Activity\ Index_t + e_t \quad (10)$$

Our findings suggest that global supply chain disruptions hurt GVA Industry growth as the coefficient of GSCDCI is negative and close to a 10 per cent significance value. However, it appears that these disruptions do not significantly affect GVA Agriculture and GVA Services after controlling for the lag of rainfall growth for agriculture GVA and the services activity index for services GVA.

Table 4.
Out-of-sample Nowcasting Models Evaluation

This table presents the out of sample performance of various nowcasting models used in the study in both pre-pandemic and post pandemic periods.

Post Pandemic Evaluation Period (2021 Q3 to 2022 Q3)				
S.No.	**Models**	**Target Variable**	**RMSE**	**Relative RMSE**
1.	Services Activity Index	GVA Services	5.02	0.90
2.	Industry Activity Index	GVA Industry	9.12	0.78
3.	Rainfall Growth	GVA Agriculture	0.70	0.92
4.	Agriculture Activity Index	GVA Agriculture	0.61	0.81
5.	Services Activity Index with Digital Index	GVA Services	5.90	1.058
6.	Industry Activity Index with Digital Index	GVA Industry	7.68	0.67
7.	Rainfall Deviation with Digital Index	GVA Agriculture	0.60	0.79
8.	Agriculture Activity Index with Digital Index	GVA Agriculture	0.85	1.26
9.	Industry Index with GSCDCI	GVA Industry	6.91	0.59
10.	Industry Index with GSCDCI and Digital Index	GVA Industry	6.40	0.55
11.	Services Index with GSCDCI	GVA Services	4.81	0.86
12.	Services Index with GSCDCI and Digital Index	GVA Services	5.52	0.99
Pre-pandemic Evaluation Period (2019 Q1 to 2019 Q4)				
S.No.	**Models**	**Target Variable**	**RMSE**	**Relative RMSE**
1.	Services Activity Index	GVA Services	1.13	0.91
2.	Industry Activity Index	GVA Industry	3.45	0.97
3.	Rainfall Growth	GVA Agriculture	2.40	1.07
4.	Agriculture Activity Index	GVA Agriculture	2.31	1.02
5.	Services Activity Index with Digital Index	GVA Services	1.49	1.20
6.	Industry Activity Index with Digital Index	GVA Industry	1.10	0.89
7.	Rainfall Deviation with Digital Index	GVA Agriculture	2.70	1.20

Table 4.
Out-of-sample Nowcasting Models Evaluation (Continued)

Pre-pandemic Evaluation Period (2019 Q1 to 2019 Q4)				
S.No.	**Models**	**Target Variable**	**RMSE**	**Relative RMSE**
8.	Agriculture Activity Index with Digital Index	GVA Agriculture	2.53	1.12
9.	Industry Index with GSCDCI	GVA Industry	4.03	1.13
10.	Industry Index with GSCDCI and Digital Index	GVA Industry	2.33	0.65
11.	Services Index with GSCDCI	GVA Services	1.10	0.89
12.	Services Index with GSCDCI and Digital Index	GVA Services	1.48	1.20

G. Out-of-sample Sectoral Nowcasting Models Evaluation

In addition to assessing the effectiveness of the various indices developed in this study for nowcasting sectoral GVA based on in-sample bridge equations regressions results, it is crucial to complement the analysis with out-of-sample evaluations. Table 4 presents the different nowcasting models used, along with their prediction errors measured in terms of Root Mean Squared Error (RMSE) and Relative RMSE using a one-period ahead rolling window method. The Relative RMSE compares the RMSE of the nowcasting model to that of the Naïve AutoRegressive (AR) Model. A Relative RMSE below 1 indicates that the augmented nowcasting model reports lower RMSE and therefore exhibits better out-of-sample forecasting ability as compared to the Naïve AR model.

Table 5.
Bridge, Almon MIDAS, and U-MIDAS Out-of-sample Evaluation

This table presents the out of sample performance of various bridging methods in both pre-pandemic and post-pandemic period.

Post Pandemic Evaluation Period (2021 Q3 to 2022 Q3)				
S.No.	**Models**	**Target Variable**	**RMSE**	**Relative RMSE**
1.	Services Activity Index under Bridge	GVA Services	5.02	0.90
2.	Services Activity Index under Almon MIDAS	GVA Services	5.6	0.90
3.	Services Activity Index under U-MIDAS	GVA Services	4.6	0.82
4.	Industry Activity Index under Bridge	GVA Industry	9.12	0.78
5.	Industry Activity Index under Almon MIDAS	GVA Industry	9.41	0.80
6.	Industry Activity Index under U-MIDAS	GVA Industry	8.85	0.76

Table 5.
Bridge, Almon MIDAS, and U-MIDAS Out-of-sample Evaluation (Continued)

Pre-pandemic Evaluation Period (2019 Q1 to 2019 Q4)				
S.No.	**Models**	**Target Variable**	**RMSE**	**Relative RMSE**
1.	Services Activity Index under Bridge	GVA Services	1.13	0.91
2.	Services Activity Index under Almon MIDAS	GVA Services	1.24	1.17
3.	Services Activity Index under U-MIDAS	GVA Services	1.58	1.27
4.	Industry Activity Index under Bridge	GVA Industry	3.45	0.97
5.	Industry Activity Index under Almon MIDAS	GVA Industry	3.01	0.84
6.	Industry Activity Index under U-MIDAS	GVA Industry	3.10	0.87

The results reported in Table 4, specifically for the sectoral activity indices, align with the findings from the in-sample regression results. The Industry and Services activity indices have a relative RMSE of less than 1 for both the pre-pandemic and post-pandemic evaluation periods, indicating that they improve nowcasting efficiency compared to the Naïve AR model. The relative RMSE for models incorporating sectoral activity indices is lower in the post-pandemic period compared to the pre-pandemic period, highlighting the growing importance of tracking coincident sectoral activity indices to monitor sectoral GVA growth. However, the RMSE of the models increased in the post-pandemic period, suggesting higher uncertainty and fluctuations in GVA growth numbers during this period, which led to higher average prediction errors compared to the pre-pandemic period.

The inclusion of the digital index in the nowcasting models yields mixed results in terms of improving forecast accuracy for Industry and Services GVA. Adding the digital index alongside the sectoral activity index in the nowcasting model for Services GVA does not result in better forecasting performance, both in the pre-pandemic and post-pandemic periods. However, incorporating the digital index improves the forecasting performance for Industry GVA in both periods, with a more significant improvement observed in the post-pandemic period. This finding is intriguing since, as discussed earlier, the digital index explained more variations in Services GVA growth compared to Industry GVA growth in the in-sample regression analysis.

The inclusion of the GSCDCI does not enhance forecast performance for Services GVA in both the pre-pandemic and post-pandemic periods. However, including the GSCDCI has improved the forecast performance for Industry GVA in the pre-pandemic period.

Regarding Agriculture GVA, in the pre-pandemic period, nowcasting models utilizing the agriculture activity index and lag of rainfall growth do not demonstrate better forecast performance than the Naïve AR model. However, in the post-pandemic period, both the agriculture activity index and lag of rainfall growth exhibit improved forecast performance compared to the Naïve AR model.

Nevertheless, this improvement could be attributed to better weather conditions and the absence of El Nino in the post-pandemic period (up to 2022), as the in-sample performance of these variables, especially the agriculture activity index, was poor.

To compare the performance of different bridging techniques such as Bridge, Almon MIDAS, and U-MIDAS, an out-of-sample evaluation was conducted using sectoral Activity Indices of Services and Industry GVA to predict their respective growth rates in both the pre-pandemic and post-pandemic periods (Table 5). Unlike the good performance of mixed frequency techniques in literature (e.g., Huber *et al*. 2023) in nowcasting economic activity during pandemic, there is no clear winner among the bridging methodologies in our study, as the results varied across periods and target variables. However, due to the simplicity and flexibility it provides, the Bridge-Averaging method can be considered superior compared to other sophisticated bridging techniques such as Almon MIDAS and U-MIDAS.

V. CONCLUSION

Following the advent of superior nowcasting methodologies (Stock and Watson 1989, and Giannone, Reichlin, and Small 2008) central bankers use these models in the quest for contemporaneous information and data-driven decision-making. The disruption to data-generating processes during the pandemic raised concerns about the effectiveness and suitability of high-frequency datasets for nowcasting macroeconomic aggregates. Our paper aims to shed light on this post-pandemic anomaly by considering the scope of (a) granular/sectoral nowcasts and combine approach; (b) incorporating new high-frequency variables, such as digital transactions and global supply chain disruption index; and (c) new bridging methodologies from high to low-frequency data.

Our findings suggest that the heterogeneity of economic shocks like COVID-19 necessitates a granular macroeconomic surveillance that includes a sector-specific approach to forecasting and nowcasting GVA, to implement sector specific targeted policy responses to economic shocks. Sectoral activity indices, combining selected HFIs, proved valuable in nowcasting sectoral GVA, except for agriculture, when compared to the Naïve AR Model.

Further, the digital activity index, constructed using various digital transaction data, aids in the real-time tracking of economic activity in the industry and services sectors. Daily real-time availability of the digital index provides early indications of GVA before the official data release.

Furthermore, the GSCDCI has limited impact on sectoral nowcasting when controlling for sectoral activity indices, though it can add value in the nowcasting Industry GVA. The choice of bridging methodologies lacks a clear winner; however, the Bridge method can be preferred over sophisticated techniques like Almon MIDAS and U-MIDAS due to its simplicity and flexibility.

Finally, our results suggest that post-pandemic nowcasting models need to be augmented appropriately by especially considering the sectoral impacts of a shock. Going forward digital footprints with play a very important role in nowcasting economic activities, and considering the global interdependence, it might be a good practice to include global supply chain indicators in the nowcasting exercise.

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