NATIONAL COUNCIL OF APPLIED ECONOMIC RESEARCH

Working Paper No.: WP 130

Nowcasting India's Quarterly GDP Growth: A Factor Augmented Time-Varying Coefficient Regression Model (FA-TVCRM)

Rudrani Bhattacharya, Bornali Bhandari, and Sudipto Mundle

October 2021

National Council of Applied Economic Research

NOWCASTING INDIA'S QUARTERLY GDP GROWTH: A FACTOR AUGMENTED TIME-VARYING COEFFICIENT REGRESSION MODEL (FA-TVCRM)

NCAER Working Paper

Rudrani Bhattacharya*, Bornali Bhandari, and Sudipto Mundle*****

Abstract

Governments, central banks, private firms and others need high frequency information on the state of the economy for their decision making. However, a key indicator like GDP is only available quarterly and that too with a lag. Hence decision makers use high frequency daily, weekly or monthly information to project GDP growth in a given quarter. This method, known as nowcasting, which started out in advanced country central banks using bridge models. Nowcasting is now based on more advanced techniques, mostly dynamic factor models. In this paper we use a novel approach, a Factor Augmented Time Varying Coefficient Regression (FA-TVCR) model, which allows us to extract information from a large number of high frequency indicators and at the same time inherently addresses the issue of frequent structural breaks encountered in Indian GDP growth. One specification of the FA-TVCR model is estimated using 19 variables available for a long period starting in 2007-08:Q1. Another specification estimates the model using a larger set of 28 indicators available for a shorter period starting in 2015-16:Q1. Comparing our model with two alternative models, we find that the FA-TVCR model outperforms a DFM model in terms of both in-sample and out-of-sample RMSE. The RMSE of the ARIMA model is somewhat lower than the FA-TVCR model within the sample period but is higher than the out-of-sample of the FA-TVCR model. Further, comparing the predictive power of the three models using the Diebold-Mariano test, we find that FA-TVCR model out-performs DFM consistently. In terms of out-of-sample forecast accuracy both the FA-TVC model and the ARIMA model have the same predictive accuracy under normal conditions. However, the FA-TVCR model outperforms the ARIMA model when applied for nowcasting in periods of major shocks like the Covid-19 shock of 2020-21.

Keywords: Nowcasting, Quarterly Year-on-Year GDP growth, State-Space Model, India.

JEL codes: C52, C53, and O40

*National Institute of Public Finance and Policy. rudrani.bhattacharya@nipfp.org.in
**National Council of Applied Economic Research. bbhandari@ncaer.org
***National Council of Applied Economic Research. sudipto.mundle@gmail.com

---

This paper is the outcome of the report which has been commissioned by South Asia Research Hub, Department for International Development, Government of UK. However, the views expressed do not necessarily reflect the UK Government's official policies.

1. Introduction

Governments, central banks, private firms and others need high frequency data on the state of the economy for their decision making. However, data on Gross Domestic Product (GDP) growth, a key indicator of the state of the economy, is typically available only on a quarterly basis and that too with a lag. In India, for example, the quarterly GDP estimate is made available with a lag of two months. Consequently, decision makers use high frequency monthly, weekly or daily information to project GDP growth for a given quarter. This method of gauging the present state of the economy using information from high frequency indicators is known as 'nowcasting.' In this paper, we propose to employ a Factor Augmented Time Varying Coefficient Regression (FA-TVCR) Model to nowcast quarterly year-on-year (y-o-y) growth in India.

Nowcasting was first introduced by central banks in the advanced economies from around 2000 and onwards. The approach initially adopted was the Bridge Model (BM) where quarterly frequency national accounts variables were regressed on their lagged values and other high frequency indicators, converted to quarterly frequency (Baffigi et al., 2004). Subsequently, more advanced techniques, mainly Dynamic Factor Models (DFMs) were developed (Giannone et al., 2008; Banbura et al, 2010). In this class of models, quarter-on-quarter GDP growth and month-on-month growth of a large set of monthly indicators are assumed to be driven by a set of unobserved factors which follow a Vector Auto Regression (VAR) structure among themselves. DFMs have been successfully implemented to nowcast GDP growth in Euro Area (Giannone et al., 2008; Banbura et al., 2010), Japan (Urasawa, 2014) and Canada (Chernis and Sekkel, 2017).

Nowcasting GDP growth has always been a challenge in emerging market economies because of the limitations of data availability, irregular release of high frequency indicators and frequent structural breaks in the data. Still, DFMs have been found to work satisfactorily for nowcasting GDP growth in countries like Brazil, Indonesia, Mexico, South Africa, Turkey, (Cepni et al., 2019; Cepni et al. 2020, Luciani et al., 2017). In India, the picture is mixed. While Bhattacharya et.al (2011) found that a bridge regression model performed better than a DFM, Bragoli and Fosten (2018) found that their DFM outperformed a bridge model. Bhadury et al. (2020) and Iyer & Sen Gupta (2020) also found DFMs to perform better compared to Random Walk and Auto Regressive Models.

In this paper, we have adopted a novel approach to address the frequent structural breaks in Indian GDP[1]. We employ a FA-TVCR model following Bhattacharya et al. (2019) and apply it using a large number of high frequency indicators to nowcast and forecast quarterly GDP growth. This model allows us to extract information from a large number of indicators and also inherently addresses the issue of frequent structural breaks in GDP growth. Comparing our model with two alternative models, we find that the FA-TVCR model outperforms a DFM model in terms of both in-sample and out-of-sample RMSE. The RMSE of the ARIMA model is somewhat lower than the FA-TVCR model within the sample period but is higher than the out-of-sample of the FA-TVCR model. Further, comparing the predictive power of

[1] Basu (2020) found four structural breaks in post-Independence India – 1964-65, 1978, 1990-91, and in 2004-05. Much of the Indian empirical literature has examined structural breaks for India pre-2011-12 (the Great Financial Recession). However, Kar & Sen (2016) and Subramanian & Felman (2019) amongst others have presented evidence of a sharp economic slowdown post 2011-12.

the three models using the Diebold-Mariano test, we find that FA-TVCR model out-performs DFM consistently. In terms of out-of-sample forecast accuracy both the FA-TVC model and the ARIMA model have the same predictive accuracy under normal conditions. However, the FA-TVCR model outperforms the ARIMA model when applied for nowcasting in periods of major shocks like the Covid-19 shock of 2020-21.

The rest of the paper is organized as follows: Section 2 explains the methodology. Section 3 describes the indicators that have been used. It should be pointed out that while monthly time series data is available for some indicators from 2004-05 onwards, some additional monthly indicators are available for shorter periods, including a few since 2014-15. Accordingly, the model has been estimated separately for two separate periods: Specification I estimates the model for the period 2007–08:Q1 to 2019–20:Q3 using only 19 indicators. Specification II estimates for the period 2015–16:Q1 to 2019–20:Q3 that includes a larger set of 28 indicators, i.e., those available since 2004–05 plus those that are available from 2014–15 onwards. Section 4 reports the estimation results. Section 5 and 6 discuss the forecast performance of the model for the pre-pandemic period Jan–Mar, 2019 to Oct–Dec, 2019, and the pandemic period from Jan–Mar, 2020 to Jan–Mar, 2021 respectively. Finally, Section 7 concludes the paper.

2. Methodology

Nowcasting of quarterly y-o-y GDP growth is essentially predicting the GDP growth for the quarter Q_t, using information from high frequency indicators (we use monthly indicators for our analysis) spanning that particular quarter Q_t. The estimation process consists of the following steps:

(i) Depending on the flow of information for the set of monthly indicators for months i, where i=1,2,3 span quarter Q_t , the nowcasting is conducted for "2 months ahead", "1 month ahead" and "zero month ahead" of GDP data release by the statistical agency of the country. Since high frequency indicators are released with different lags on different dates in a month, addressing the "ragged-edge data" problem at the end of the sample period is a major challenge in the nowcasting methodology. Converting monthly indicators into quarterly frequency by forecasting the observation/s unavailable for the month/s in a particular quarter is a commonly used method of handling the ragged-edge data problem.[2]

(ii) When a monthly indicator Y_i is available till month i=1 in quarter Q_t, we forecast the values for i=2 and 3 in quarter t using Seasonal ARIMA (p,d,q)(P, D, Q) model:

$$\phi(L)\Phi(L^s)(1-L)^d(1-L^s)^D Y_i = \theta(L)\Theta(L^s)\epsilon_i \dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

where L is the lag operator ($LY_i = Y_{i-1}$); s is the seasonal period and hence s=12 for monthly data; $\phi(L) = 1 - \phi_1 L\text{-}\phi_2 L^2 - \cdots . -\phi_p L^p$ is the non-seasonal

[2] Since this method attaches equal weights to all the monthly observations in a quarter, more complex weighting schemes, widely known as "Mixed Data Sampling (MIDAS)" method (Marcellino and Schumacher, 2010; Forni and Marcellino, 2014). This method has been applied to both regression and DFM structure. We are unable to apply his method in India because of the paucity of data.

autoregressive (AR) operator; $\Phi(L) = 1 - \Phi_1 L\text{-}\Phi_2 L^{2s} - \cdots . -\Phi_P L^{Ps}$ is the seasonal AR operator; $\theta(L) = 1 - \theta_1 L\text{-}\theta_2 L^2 - \cdots . -\theta_q L^q$ is the non-seasonal moving average (MA) operator; and $\Theta(L) = 1 - \Theta_1 L\text{-}\Theta_2 L^2 - \cdots . -\Theta_Q L^Q$ is the seasonal MA operator. Similarly, d represents the number of differencing required to remove the non-seasonal unit root. Here ϵ_i is the $i.i.d$ error with zero mean and variance σ^2. The Seasonal ARIMA structure is optimally chosen using X13–SEATS Seasonal Adjustment Programme of U.S. Census Bureau. Again, when a monthly indicator Y_i is available till month i=1 and 2 in quarter Q_t, we forecast the values for i=3 in quarter Q_t using the same method. Forecasting is not conducted when information on a monthly indicator is available for all the three months spanning quarter Q_t.

(iii) Once information for all the three months spanning the quarter Q_t are obtained, the monthly series is converted to quarterly frequency. The quarterly y-o-y growth of the indicator is then derived.

(iv) Assuming that a set of unobserved factors determines performance of the economic observed in the dynamics monthly indicators, the static factors are estimated from Y-o-Y growth in the set of monthly indicators converted to quarterly frequency using Principal Component Analysis (Stock and Watson, 2020). The first k numbers of factors which explain at least 80 per cent of variation in the data are chosen. The weighted sum of estimated factors provides a single composite indicator where weights are the share of variance of each factor in total variation.

(v) Next, we regress quarterly y-o-y growth in GDP available till quarter Q_{t-1} on the k number of factors till quarter Q_{t-1} and one period lagged GDP growth where the regression coefficients are assumed to vary over time. Finally, using the estimated coefficient and the values of k factors obtained for the quarter Q_t from the set of monthly indicators, the nowcast of the GDP growth for Q_t is obtained.

The details of the regression model are as follows:

Measurement equation:

$$y_t = X_t' \beta_t + \epsilon_t \qquad (2)$$

where X_ts is a (k+1 × 1) vector consisting of k number of chosen factors F_t and one quarter lagged GDP growth.

Transition equation

$$(\beta_{t+1} - \bar{\beta}) = \mathbf{G}(\beta_t - \bar{\beta}) + \mathbf{v}_{t+1} \qquad (3)$$

If the eigen values of the (k+1×k+1) matrix G are all inside the unit circle, then β has the interpretation as the average or steady-state value for the coefficient vector.

Assuming that,

$$\begin{pmatrix} V_{t+1} \\ \epsilon_t \end{pmatrix} | X_{t,z_{t-1}} \Big) \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & \sigma^2 \end{pmatrix} \right] \qquad (4)$$

where $z_{t-1} \equiv (y_{t-1}', y_{t-2}', \ldots\ldots, y_1', X_{t-1}', X_{t-2}', \ldots\ldots\ldots\ldots, X_1')'$

Here the regression coefficients β are not unknown constants but latent, stochastic variables that follow random walks, estimated by Kalman Filter (Hamilton,1994; Kim and Nelson,1999). Equations 2,3, and 4 represent the state-space form of the time-varying parameter model, with state vector $\mathbf{s}_t = \beta_t - \bar{\beta}$.

The measurement equation can then be re-written as

$$y_t = X_t'\bar{\beta} + X_t'\mathbf{s}_t + \epsilon_t \tag{5}$$

which is an observation equation with $\mathbf{a}(\mathbf{X_t}) = X_t'\bar{\beta}$, $\mathbf{H}(\mathbf{X_t}) = \mathbf{X_t}$, and $\mathbf{R}(\mathbf{X_t}) = \sigma^2$. These values then used in the following Kalman Filter iterations (see Hamilton (1994) for details):

$$\hat{s}_{t|t} = \hat{s}_{t|t-1} + \{P_{t|t-1}H(X_t)[H(X_t)']P_{t|t-1}H(X_t) + R(X_t)]^{-1} \times [y_t - a(X_t) - H(X_t)'] \, \hat{s}_{t|t-1}\} \tag{6}$$

$$P_{t|t} = P_{t|t-1} - \{P_{t|t-1} \, H(X_t)\} \times [H(X_t)']P_{t|t-1} \, H(X_t) + R(F_t)]^{-1} H(X_t)'P_{t|t-1} \} \tag{7}$$

$$s_{t+1}|X, z_{t-1} \sim N(\hat{s}_{t+1|t}, P_{t+1|t}) \tag{8}$$

$$\hat{s}_{t+1|t} = G\hat{s}_{t|t} \tag{9}$$

$$P_{t+1|t} = GP_{t|t}G' + Q \tag{10}$$

3. The Data

The target variable in our analysis is the quarterly y-o-y growth rate of the aggregate GDP in India. The GDP data are sourced from the Central Statistical Organisation, Ministry of Statistics and Programme Implementation (CSO, MOSPI) for the period 2004–05: Q1, to 2020–21:Q4.[3] In its quarterly GDP estimates, MoSPI regularly publishes the indicators which are used to estimate it. We have used the same set of indicators plus some additional indicators, mostly drawn from Centre for Monitoring Indian Economy (CMIE). The high frequency dataset consists of 29 monthly indicators which have been listed in Appendix A.

The monthly indicators are taken for the period April 2004 to February 2021. The data sources, along with their date of periodic release are given in Appendix A, Table A.1.

We test for stationarity of quarterly y-o-y growth rates of the high frequency indicators using Augmented Dickey-Fuller (ADF) test and Phillips-Perron (PP) test with the null hypothesis of presence of unit root in the series. We also employ Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test with the null hypothesis that the series is stationary around a constant or a deterministic trend against the alternative hypothesis that the series contains unit root. All variables are found to be stationary

---

[3] In India, the financial year calendar starts from 1st April of a particular calendar year to 31st March of the following year. Thus 2004-05: Q1 refers to the April-June quarter in the year 2004. In this paper we have followed the Indian financial year calendar.

by either one or both the tests, except for CPI inflation and growth in cargo movement by air.[4]

4. Model Estimation

Since India experienced a massive contraction shock in the 2020–21 due to the COVID–19 pandemic, we first estimate our model till the period ending at Oct–Dec 2019, i.e., before the outbreak of the pandemic, and evaluate the model performance till that period. , We then assess the performance of the model for the pandemic period i.e., Jan–Mar 2020 to Jan–Mar 2021.

As a first step, we apply static factor analysis to summarise the information about the performance of the economy from quarterly y-o-y growth rates of monthly indicators converted to quarterly frequency. The full sample or long period analysis in Specification I includes 19 high frequency indicators.

The factors extracting information from these 19 indicators are then estimated using Maximum Likelihood Method. The number of factors estimated are 3.[5] Table 1 reports factor loadings, i.e., the correlation of each of the indicators with the estimated latent factors. The factor loadings give the variance explained by the data associated with each factor. As a rule of thumb, in our analysis a factor loading with value 0.6 or more is taken to indicate that the factor extracts sufficient variation from that variable. Table 1 suggests that the factor F1 extracts variations from growth in aggregate deposits, food and non-food credit, exports of goods and GST revenue.

Table 1: Loadings of variables in estimated factors

Variable (Y-o-Y growth, %)	***F1***	***F2***	***F3***
Passenger Car Sales	0.31	0.26	0.60
Cargo Handled in Ports	0.03	0.87	0.04
CPI	0.45	(–)0.30	0.46
Aggregate Deposits	0.77	0.18	(–)0.04
Electricity Demand	0.24	0.13	0.20
Exports of Goods	0.58	0.05	0.37
Food Credit	0.59	(–)0.38	(–)0.07
GST	0.62	0.31	0.53
IIP	0.43	0.85	0.22
Non-food Credit	0.98	0.13	0.08
Non-oil Imports of Goods	0.47	(–)0.04	0.23
NSE Turnover	(–)0.16	0.61	0.004
Deviation of Rain from Normal Level	0.10	0.08	(–)0.14
Revenue Expenditure (Net of Interest Payments)	0.31	(–)0.14	(–)0.20
Rice Production	0.15	0.12	0.07
Net Tax Revenue	0.15	0.36	0.23
No. of Tourists Arrival in India	(–)0.04	0.52	0.24
Production of Two Wheelers	(–)0.07	(–)0.002	0.91
Production of Commercial Vehicles	(–)0.01	0.36	0.76

Source: Authors' estimates.

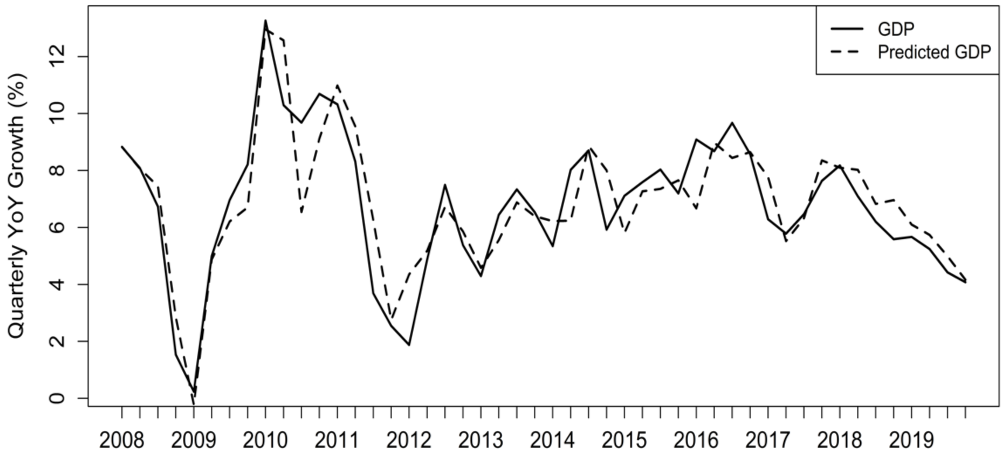
[4] The unit root test results are available from the authors on request.
[5] We choose all the three factors as only 78 per cent of the variation is explained by the first two factors.

The factor F2 extracts variations from the growth in cargo handled in major sea ports, Index of Industrial Production (IIP), National Stock Exchange (NSE) turnover and the indicator for tourism. Finally, the factor F3 extracts variations from the growth in car sales, production of two wheelers and the production of commercial vehicles.

Next, Equation (2) is estimated where GDP growth is regressed on F1, F2, F3 and one period lagged GDP growth. The coefficients are assumed to vary over time and are estimated in a state-space framework, using Kalman filtration technique. Figure 1 depicts actual GDP growth along with the estimated GDP growth for the sample period Jan–Mar 2008–Oct–Dec 2019. The figure shows that predicted GDP growth using FA-TVCR model captures most of the turning points in Indian GDP growth series for the full sample period quite well.

Figure 1: Actual and Predicted GDP Growth

(Jan–Mar 2008–Oct–Dec 2019)



Source: Authors' estimates.

In the second exercise, Specification II, we incorporate a few additional variables which are available for a shorter sample period. Information from a total of 28 high-frequency indicators is used in this exercise. The number of factors estimated is 3. However, given the limited number of observations in this exercise, only the first factor explaining 71.5 per cent variation in the data is considered for the time-varying coefficient regression model (see Table 2)[6].

The factor loadings reported in Table 2 suggests that the first factor extracts variations from transport services indicators such as cargo movements via sea, air and rail, and passengers travelling by air; production indicators such as IIP, production of coal and cement, production of two wheelers and commercial vehicles; trade indicators such as exports of goods and services, and non-oil imports of goods and

[6] Given that the data on consumption of finished steel products are available from December 2013, the quarterly y-o-y growth of this indicator is available from the quarter Jan-Mar 2015. Consequently, we have 24 observations for each of 28 indicators. Since the number of observations is less than the number of variables, the factor matrices are rank deficient and hence ML Estimator technique is not applicable (Robertson and Sumons, 2007). Hence we apply Iterated Principal Factor method in this stage.

services; electricity demand and supply; other demand indicators such as car sales, fiscal indicators such as net tax revenue and consolidated GST revenue.

Table 2: Loadings of variables in estimated factors: Jan–Mar, 2015 onwards

Variable (Y-o-Y growth, %)	***F1***
Cargo Movement by Air	0.78
Passengers Travelled by Air	0.58
Car Sales	0.83
Cargo Handled in Ports	0.75
Production of Coal	0.74
Production of Cement	0.83
CPI	(–)0.31
Aggregate Deposits	(–)0.20
Electricity Supply	0.82
Electricity Demand	0.85
Exports of Goods and Services	0.57
Food Credit	(–)0.39
GST	0.89
IIP	0.90
Non-food Credit	0.40
Non-oil Imports of Goods and Services	0.78
NSE Turnover	(–)0.09
Production of Crude Oil	0.39
Deviation of Rain from Normal Level	(–)0.46
Revenue Expenditure (Net of Interest Payments)	(–)0.07
Rice Production	0.13
Goods Movement via Rail	0.90
Passengers Travelled by Rail	0.47
Net Tax Revenue	0.57
Telephone/Mobile Subscribers	0.13
Domestic Sale of Tractors	0.42
Production of Two Wheelers	0.96
Production of Commercial Vehicles	0.89

Source: Authors' estimates.

5. Forecast Performance of FA-TVCR Model

5.1 Forecast performance of FA-TVCRM for Specification I: Using indicators available from 2004–05

In order to evaluate the in-sample and out-of-sample performance of the model, we divide the sample period into trend data and test data periods, respectively. The trend data period is Apr–Jun, 2007 to Oct–Dec 2018. The test data period is Jan–Mar,2019 to Oct–Dec 2019. We estimate the model for the trend data period using the

FA-TVCR model Specification I and the in-sample Root Mean Square Error (RMSE) is found to be 0.39.[7]

We then obtain the out-of-sample period nowcasts for the four quarters of 2019 in the following way. With the model estimated till Oct–Dec 2018, the nowcast of GDP growth for Jan–Mar 2019 is obtained using the estimated coefficients and the factors summarizing information from high frequency indicators available for the quarter Jan–Mar, 2019. The model is then re-estimated with data till Jan-Mar 2019 and the nowcast for Apr-Jun 2019 is obtained using the re-estimated parameters and the factors estimated using monthly indicators for Apr-Jun 2019. We repeat this procedure to obtain nowcast of GDP growth for the quarter Oct-Dec 2019. The out of sample RMSE turns out to be 0.33.

Table 3 compares the in-sample nowcast performance of the FA-TVCR model Specification I with two alternative models, namely a Dynamic Factor Model (DFM) and a univariate ARIMA model.[8]

Table 3: Comparing in-sample forecast performance of FA-TVCR model Specification I and alternative models

Model	***In-sample RMSE***	***DM Test H0: Two forecasts have same predictive accuracy H1: Two forecasts have different predictive accuracy***		***DM Test H0: Two forecasts have same predictive accuracy H1: Forecast 1 is more accurate than forecast 2***	
		Test Statistic	p-value	Test statistic	p-value
FA-TVCRM	0.39				
DFM	0.49				
ARIMA	0.08				
FA-TVCRM vs. DFM		(–)2.581	0.010	(–)2.581	0.005
FA-TVCRM vs. ARIMA		(–)1.554	0.120	(–)1.554	0.060

Source: Authors' estimates.

In terms of in-sample RMSE, ARIMA performs best with the lowest RMSE, followed by the FA-TVCR model Specification I and DFM (Table 3). However, when we compare the predictive power of FA-TVCR Specification I and ARIMA models using the Diebold-Mariano test (Diebold and Mariano, 1995), the null hypothesis is rejected against the alternative hypothesis that nowcast from FA-TVCRM is more accurate than the nowcast from the ARIMA model (Table 3 row 5, columns 2 to 5).

Further, when we further compare the predictive power of FA-TVCR model with DFM using Diebold-Mariano test, the null hypothesis that the two models have the same

[7] The model is estimated with the indicators standardized using their respective mean and standard deviation which is a standard practice in the estimation of forecasting models.
[8] The details of the DFM is given in Appendix B.

predictive accuracy is rejected at 5 per cent level of significance against the alternative hypothesis that the two models have different accuracy as well as against the alternative hypothesis that nowcast from FA-TVCR model is more accurate than the nowcast from DFM (row 4, columns 2 to 5 in Table 3).

In terms of out-of-sample RMSE, FA-TVCR model performs best followed by ARIMA model and DFM (Table 3). Using the Diebold-Mariano test, we reject the null hypothesis that FA-TVCRM and DFM have same predictive accuracy against the alternative hypothesis that the out-of-sample nowcast from FA-TVCRM is more accurate than the out-of-sample nowcast from DFM (row 4, columns 2 to 5 in Table 4). However, we cannot reject the null hypothesis that the predictive accuracy of the FA-TVCRM and the ARIMA model are the same.

Table 4: Comparing out-of-sample forecast performance of alternative models

Model	***Out-of-sample RMSE***	***DM Test H0: Two forecasts have same predictive accuracy H1: Two forecasts have different predictive accuracy***		***DM Test H0: Two forecasts have same predictive accuracy H1: Forecast 1 is more accurate than forecast 2***	
		Test Statistic	*p-value*	*Test statistic*	*p-value*
FA-TVCRM Specification I	0.33				
DFM	0.80				
ARIMA	0.47				
FA-TVCRM Specification I vs. DFM		(–)5.450	0.012	(–)5.450	0.006
FA-TVCRM Specification I vs. ARIMA		(–)1.401	0.256	(–)1.401	0.128

Source: Authors' estimates.

6. Performance of the Models for the Period including COVID–19 Pandemic

We next investigate the nowcast performance of the model for the period including the COVID–19 pandemic when the economy was hit by massive negative shocks. We estimate both the specifications of FA-TVCR model and the ARIMA model. We then test the in-sample and out-of-sample nowcast performance of all the three (Table 5).

The in-sample RMSE for the ARIMA model is the lowest of the three at 1.05. However, it is the highest of the three at 2.7 for the out-of-sample period. Both specifications of our FA-TVCR model also perform better than the ARIMA model in terms of the D-M test.

Comparing between the two specifications of FA-TVCR model, we find that both the in-sample RMSE and out-of-sample RMSE for Specification I is lower than that of Specification II. However, if we exclude the post-lockdown quarter of Apr–Jun 2020 when the Indian economy recorded the largest contraction ever of 24.4 per cent, the out-of-sample RMSE of Specification II is found to be 0.12, substantially lower than 0.43 per cent of Specification I. Further, while Specification I better predicts the contraction of Apr–Jun, 2020, Specification II predicts the recovery pattern better. Finally the DM test suggests that both the specifications have the same accuracy, implying that the model is robust and its predictive power is invariant with respect to the length of the time series or the number of indicators used.

Table 5: Comparing out-of-sample forecast performance of alternative models for the period including the COVID–19 pandemic

Model	***In-sample RMSE for period upto Jan–Mar, 2021***	***Out-of-sample RMSE (Jan–Mar, 2020 to Jan–Mar, 2021)***	***Out-of-sample RMSE upto Jan–Mar, 2021, excluding Apr–Jun, 2020***	***DM Test Ho: Two forecasts have same predictive accuracy H1: Two forecasts have different predictive accuracy***		***DM Test Ho: Two forecasts have same predictive accuracy H1: Forecast 1 is more accurate than forecast 2***	
				Test Statistic	p-value	Test statistic	p-value
FA-TVCRM Spc I	1.07	1.8	0.43				
FA-TVCRM Spc II	1.23	2.2	0.12				
ARIMA	1.05	2.7					
FA-TVCRM Spc I vs. ARIMA (Q1 2020-Q1 2021)				(–)2.4612	0.070	(–)2.4612	0.035
FA-TVCRM Spc II vs. ARIMA (Q1 2020-Q1 2021)				(–)2.363	0.077	(–)2.363	0.039
FA_TVCRM Spc I vs. SPC II				0.890	0.423	0.890	0.788

Source: Authors' estimates.

7. Conclusion

Governments, central banks, private firms and others need high frequency data on the state of the economy for their decision making. However, a key indicator like GDP is only available quarterly and that too with a lag. Decision makers have therefore adopted the technique of nowcasting, projecting quarterly GDP based on high frequency daily, weekly or monthly indicators, mostly based on DMS models. In this paper we have presented an alternative model, the FA-TVCR nowcasting model which allows us to extract information from a large number of indicators and also inherently addresses the issue of frequent structural breaks in GDP growth. This model has been estimated for a full sample period from Jan–March 2007 to October–December 2018 using 19 high frequency indicators (Specification I) and for a shorter sample period from April–June 2015 to October–December 2018 using a larger set of 28 indicators which are available for this shorter period (Specification II).

When comparing, we find that the FA-TVCR model is robust in the sense that Specification I using a fewer set of indicators for a longer period and Specification II which uses a larger set of indicators for a shorter period are equally efficient in terms of predictive power. We also find that our model outperforms a DFM and a univariate ARIMA model in terms of both in-sample and out-of-sample RMSE. Comparing the predictive power of the three models using the Diebold-Mariano test, we find that the FA-TVCR model out-performs DFM consistently. Both, our model and the ARIMA model have the same predictive accuracy in terms of out-of-sample forecast accuracy under normal conditions. However, our model outperforms the ARIMA model when applied for nowcasting during a period including the Covid-19 pandemic shock. It suggests that the FA-TVCR model is a more appropriate tool for nowcasting GDP in countries characterised by frequent structural breaks and large shocks.

References

Alberto Baffigi, Roberto Golinelli and Giuseppe Parigia. 2004, "Bridge Models to Forecast Euro Area GDP," *International Journal of Forecasting*, 20: 447-460.

Marta Bańbura, Domenico Giannone, and Lucrezia Reichlin. 2010. "Nowcasting," European Central Bank, Working Paper Series No. 1275, December.

Deepankar Basy.2020. "Revisiting India's Growth Transitions" (2020). UMass Amherst Economics Working Papers. 284. https://doi.org/10.7275/16097049.

Soumya Bhadury, Saurabh Ghosh, and Pankaj Kumar. 2020. "Nowcasting Indian GDP growth using a Dynamic Factor Model", RBI Working Paper Series No. 3, February. Department of Economic and Policy Research, Reserve Bank of India, Mumbai.

Rudrani Bhattacharya, Radhika Pandey, and Giovanni Veronese. 2011. "Tracking India Growth in Real Time," National Institute of Public Finance and Policy, Working Paper No. 2011-90, July.

Rudrani Bhattacharya, Parma Chakravartti, and Sudipto Mundle. 2019. "Forecasting India's Economic Growth: A Time-Varying Parameter Regression Approach," *Macroeconomics and Finance in Emerging Market Economies*, 12 (3): 205-228.

Daniela Bragoli and Jack Fosten. 2018. "Nowcasting Indian GDP," *Oxford Bulletin of Economics and Statistics*, 80 (2): 259–282.

Oguzhan Cepni, I. Ethem Güney, and Norman R. Swanson 2019. "Nowcasting and Forecasting GDP in Emerging Markets using Global Financial and Macroeconomic Diffusion Indexes," *International Journal of Forecasting*, 35 (2): 555–572, April-June.

Oguzhan Cepni, I. Ethem Güney, and Norman R. Swanson. 2020. "Forecasting and Nowcasting Emerging Market GDP Growth Rates: The Role of Latent Global Economic Policy Uncertainty and Macroeconomic Data Surprise Factors," *Journal of Forecasting*, 39 (1): 18–36, January.

Tony Charnis and Rodrigo Sekkel. 2017. "A Dynamic Factor Model for Nowcasting Canadian GDP Growth," *Empirical Economics*, 53 (1): 217–234.

Diebold, F. X. and Mariano, R. S. 1995. Comparing Predictive Accuracy. *Journal of Business and Economic Statistics* 13 (3): 253–263, July.

Claudia Foroni and Massimiliano Marcellino. 2014. "A Comparison of Mixed Frequency Approaches for Nowcasting Euro Area Macroeconomic Aggregates," *International Journal of Forecasting*, 30 (3): 554–568.

Francis Diebold and Robert Mariano. 2002. "Comparative Predictive Accuracy", *Journal of Business & Economics Statistics*, 20 (1): 134–44.

Domenico Giannone, Lucrezia Reichlin, and David Small. 2008. "Nowcasting: The Real Time Informational Content of Macroeconomic Data," *Journal of Monetary Economics*, 55 (4): 665–676, May.

J. D. Hamilton. 1994. Time Series Analysis. Princeton University Press.

Tara Iyer and Abhijit Sen Gupta. May 2020. "Nowcasting Economic Growth in India: The Role of Rainfall," Asian Development Bank Economics Working Paper Series No. 593, May.

S. Kar and Sen, K. 2016. The Political Economy of India's Growth Episodes. Palgrave Pivot, London.

C. J. Kim and C.R. Nelson. 1999. "State Space Models with Regime Switching: Classical and Gibbs Sampling Approaches with Applications." MIT Press.

Matteo Luciani, Madhavi Pundit, Arief Ramayandi, and Giovanni Veronese. 2018. "Nowcasting Indonesia," *Empirical Economics*, 55 (2): 597-619.

Massimiliano Marcellino and Christian Schumacher. 2010. "Factor MIDAS for Nowcasting and Forecasting with Ragged-Edge Data: A Model Comparison for German GDP**,"** *Oxford Bulletin of Economics and Statistics*, 72 (4): 518–550.

Donald Robertson and James Symons. 2007. "Maximum Likelihood Factor Analysis with Rank-Deficient Sample Covariance Matrices," *Journal of Multivariate Analysis*, 98 (4): 813–828.

James H Stock and Mark W Watson. 2002. "Forecasting Using Principal Components from a Large Number of Predictors," *Journal of American Statistical Association*, 97 (460)1167–1179, December.

Satoshi Urasawa, (2014), "Real-time GDP Forecasting for Japan: A Dynamic Factor Model Approach," *Journal of the Japanese and International Economics*, 34: 116–134.

Arvind Subramanian and Josh Felman. 2019. "India's Great Slowdown: What Happened? What's the Way Out?", *CID Faculty Working Paper No. 370*, December. Harvard University, https://www.hks.harvard.edu/sites/default/files/centers/cid/files/publications/faculty-working-papers/2019-12-cid-wp-369-indian-growth-diagnosis-remedies-final.pdf,

Appendix A

Sector	***Series***	***Source***	***Web link***	***Date of release***	***Notes***
Agriculture	Rainfall	CMIE		1st of every month	Deviation from long period average rainfall is more important determinant of agricultural output than absolute rainfall level
	Domestic Sale of Tractors	Tractors Manufacturers Association	https://www.tmaindia.in/consolidated-monthly-reports-2021.php	Mid-month	Used only in Specification II of FA-TVCR Model
	Production of Rice	Department of Agriculture	https://eands.dacnet.nic.in/	No fixed date	
Industry	IIP (2011-12 base)	CSO, MOSPI	http://mospi.nic.in/iip	12th of every month	Data are published with a two months lag
	IIP (2004-05 base)	CSO, MOSPI	http://mospi.nic.in/iip		Used for Specification I of FA-TVCR Model and DFM
	Production of two wheelers	MoSPI Micro data	http://microdata.gov.in/nada43/index.php/catalog/148	12th of every month	Data are published with a two months lag
	Production of commercial vehicles	MoSPI Micro data	http://microdata.gov.in/nada43/index.php/catalog/148	12th of every month	Data are published with a two months lag
	Passenger car sales	CMIE		11th of every month	Used in DFM and FT-TVCR Model
	Production of Coal	Office of Economic Adviser	https://eaindustry.nic.in/	30th of every month	Used only in Specification II of FA-TVCR Model
	Production of Crude Oil	Office of Economic Adviser	https://eaindustry.nic.in/		”
	Production of Cement	Office of Economic Adviser	https://eaindustry.nic.in/		”
	Consumption of Steel	CMIE		Mid-month	”
	Electricity Generation	CMIE		End-of-month	”
	Imports of oil (Rs)	Press release of Ministry of Commerce and Industry	https://pib.gov.in/PressReleaseIframePage.aspx?PRID=1704910	15th of a month	Used in DFM and FT-TVCR Model
Services	Total Telephone Subscribers	Telephone Regulatory Authority of India	https://trai.gov.in/release-publication/reports/telecom-subscriptions-reports	No fixed date	Published with 2 months lag Used only in Specification II of FA-TVCR Model
	Foreign tourists arrival in India	Ministry of Tourism Press Release	https://tourism.gov.in/market-research-and-statistics	No fixed date	Used for Specification I of FA-TVCR Model and DFM
	Cargo handled at major sea ports	Ministry of Ports, Shipping and Waterways	http://www.ipa.nic.in/	1st week of every month	Used in DFM and FT-TVCR Model
	Cargo handled at airports ('000 tonnes)	CMIE		Third week of every month	Used only in Specification II of FA-TVCR Model
	Number of air travel passengers (lakh)	CMIE		Third week of every month	Used only in Specification II of FA-TVCR Model
	Number of rail travel passengers (millions)	CMIE		First week of every month	Used only in Specification II of FA-TVCR Model
	Cargo handled at railways ('000 tonnes)	CMIE		First week of every month	Used only in Specification II of FA-TVCR Model

Sector	***Series***	***Source***	***Web link***	***Date of release***	***Notes***
	Average Daily Turnover at NSE	National Stock Exchange	https://www1.nseindia.com/products/content/equities/equities/historical_equity_businessgrowth.htm	Weekly	Used in DFM and FT-TVCR Model
Prices	CPI-IW (2001 base)	Labour Bureau/	http://labourbureau.gov.in/LBO_indexes.htm	Last week of every month	Used for Specification I of FA-TVCR Model and DFM
	CPI-IW (2016 base)	Labour Bureau/CMIE	http://labourbureau.gov.in/LBO_indexes.htm		Used for Specification I of FA-TVCR Model and DFM
	CPI (base 2011-12)	CSO, MOSPI	http://164.100.34.62:8080/Default1.aspx	12th of every month	Used in DFM and FT-TVCR Model
External Sector	Exports of goods (Rs crore)	Department of Commerce, Ministry of Commerce & Industry	https://commerce.gov.in/trade-statistics/	15th of every month	Used for Specification I of FA-TVCR Model and DFM
	Imports of non-oil goods (Rs crore)	"	"	"	"
	Exports of Goods and Services (Rs crore)	"	"	"	Used only in Specification II of FA-TVCR Model
	Imports of non-oil goods and Services (Rs crore)	"	"	"	"
Fiscal Indicators	Net tax revenue (Rs crore)	Controller General of Accounts	http://www.cga.nic.in/	30th of every month	
	Revenue Expenditure Net of Interest Payments (Rs crore)				
	GST Collection (Rs crore)	PIB, Ministry of Finance	https://pib.gov.in/SearchResults.aspx?q=GST&cx=003919640075425102515%3a4lg1hrnhj_k&cof=FORID%3a9#gsc.tab=0&gsc.q=GST&gsc.page=1	1st of every month	Backcast as proxy for indirect taxes Used in DFM and FT-TVCR Model
Monetary Indicators	Food Credit (Rs crore)	RBI Weekly Statistical Supplement	https://rbi.org.in/scripts/BS_ViewWSS.aspx	2nd Friday of a month	Used in DFM and FT-TVCR Model
	Non-food Credit (Rs crore)	"	"	"	"
	Aggregate Bank Deposits (Rs crore)	"	"	"	"
Energy Demand	Electricity Requirements	CMIE		Daily	Used in DFM and FT-TVCR Model

Appendix B

1. Dynamic Factor Model

The Dynamic Factor Model (DFM) assumes that a common unobservable state variable s_t drives N number of macroeconomic indicators y_t. The framework of Dynamic Factor Model (DFM) is outlined as follows:

$$y_t = As_t + By_{t-1} + e_t \qquad \text{(B.1)}$$

$$s_t = C + \varphi s_{t-1} + u_t \qquad \text{(B.2)}$$

where y_t is $(N \times 1)$, s_t is $(K \times 1)$, A is $(N \times K)$, B is $(N \times N)$ and φ is

$(K \times K)$. Here A, B, C are parameters to be estimated and e_t and u_t are modelled as Gaussian error terms $e_t \sim iid\ N(0, R)$, $u_t \sim iid\ N(0, Q)$, and $E(e_t u_t) = 0$.

The DFM specification is a state-space model where the first equation, the measurement equation, describes the relation between the observed variable y_t and the unobserved state variable s_t. Equation (B.1) is the transition equation which describes the dynamics of unobserved variables. All the variables in the model are required to be stationary.

The model estimation aims at estimating the parameters A, B, C and φ to recover the unobserved state space variable s_t. The model is estimated using Kalman filtering technique which is a recursive algorithm that provides an optimal estimate of s_t conditional on information up to time $t-1$ and knowledge of the state space parameters A, B, C, φ, R

NATIONAL COUNCIL OF APPLIED ECONOMIC RESEARCH

NCAER India Centre, 11 Indraprastha Estate, New Delhi 110002. INDIA.
Tel: +91-11-2345 2698, 6120 2698 Email: info@ncaer.org www.ncaer.org

NCAER | Quality . Relevance . Impact