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Abstract

This paper attempts to estimate long-run forecasting of Indian GDP for the post-COVID period using the factor error correction model (FECM). The model builds on a dynamic factor model that directly and indirectly captures many dimensions affecting the cycles of a macro variable. Availability of big data enables the extraction of some common factors from large dimensions, which essentially produces better precision of forecasting estimates. The method first extracts leading factors and then add proxy policy variables to establish their long-run relationship with the GDP and produces insignificant in-sample bias. The relationship has been employed to predict GDP for 2022-35. We found three major dynamic factors that capture 80% of variations of 56 quarterly variables of the Indian economy. These three factors with four lags and four exogenous policy instruments have been included in the FECM model for forecasting estimation. We find that the economy is expected to grow at 4-8% annually, depending upon the actual realisation of external shocks and policies. The expected rise of temperature and oil price seems to be dampening the growth. But, the institutional reforms making effective public investment and the introduction of digital currency that reduces cash requirements could play an expansionary role. If the oil price and the temperature remains at the current level, the growth rate can go closer to 8%.

JEL Code: C53, O40

Key words: Forecasting, Dynamic Factor Model, FECM, ARIMA, India

1 Introduction

The growth of the Indian economy during the last decade, especially after the global financial crisis, was lagging behind the gloomy period of the 2000s. On top of it, the COVID pandemic and associated lock-down restrictions have severely hit the growth momentum during 2020 and 2021. Before the pandemic, the economy was already crippling with the real sector crisis, significant non-performing assets of the banking sector, rising petroleum prices, and a huge unemployment problem. The lower repo rate and higher budget deficits have further squeezed the capacity to exercise the expansionary fiscal and monetary policies to deal with these issues. Still, a couple of reform measures, in the form of monetisation, disinvestment strategies, and institutional, tax and labour reforms, that could boost the industrial and economic activities have been undertaken to handle these situations. Once the economy starts getting into full swing after the lock-down restrictions, one would be interested to know the path of long-run recovery. It is difficult to predict the growth path for a long-run period, both for methodology and variable choices. Still, an attempt has been made to understand a broad outline and consider instruments that may play a critical role in influencing the pace of growth. Some external factors and policy innovations in the financial and fiscal strategies may also affect the speed of recovery. For example, the temperature rise may accelerate the extreme climatic events in the economy and hence is expected to destroy incomes to a certain extent (Krishnan et al., 2020). Similarly, crude oil prices have started to rise and generated inflationary pressure in the economy. And, it is expected to shoot up further as a result of recent Russia and Ukraine War. Alternative sources of oil would shrink after a decade. In parallel, the Indian government is engaged in undertaking a series of institutional reforms through digitalisation, which may improve the efficiency of fiscal instruments. Moreover, the Reserve Bank of India has decided to launch a digital currency to deal with the corruption and improve the transmission mechanism of monetary policy instruments, and this may reduce the need for cash holding and serve as an expansionary instrument (Handa, 2020). Suitable proxies have been considered in the exercise to feed into the recovery path. Before the financial crisis, the Indian economy consistently maintained two-digit growth rates under normal circumstances. So, the economy could expect to grow at least 10% on an average during the next one and half decades. By accommodating some of these expected external shocks and policy innovations, this forecasting exercise aims to investigate to what extent it may achieve the expected level and what can be done to reach the target.

Forecasting long-run growth is challenging due to the unavailability of a robust methodology and a clear strategy to deal with unobserved exogenous shocks and policy variables. Hence, two methodological issues should be dealt with for meaningful forecasting. First, the dynamics of macroeconomic variable, like GDP, depends on various known and unknown variables. Many of them are highly correlated. If they are ignored, forecasting may not be a meaningful exercise. The traditional econometric methods that employ a few variables ignore many of them and thereby miss a large set of information. Hence, there is a growing interest to use big data to capture as much information as possible for forecasting them. But, big data may reduce the precision power of econometric models. As a result, applying factor models that reduce the dimensions of big data by extracting the common factors helps explain the business cycles to a greater extent. Such methods have been the growing practice for forecasting macro-variables. The larger the data set, the more the information and better would be forecasting results. Moreover, the standard econometric techniques built on classical macro-models using a few variables are becoming less credible to predict business cycles, especially after financial cycles. As a result, the current paper attempted to forecast the Indian GDP for a relatively more extended period using the Factor-augmented Error Correction Model (FECM). This model first extracts the information from big data using the dynamic factor model and then establishes a long-run relationship using the error-correction model for forecasting (Banerjee and Marcellino, 2009; Banerjee et al., 2014). Second, the forecasting estimation did not consider any exogenous and policy variables. We believe that the long-run prediction should include a few to infer the policy impacts. As a result, four exogenous variables found at the I(0) series have been added to the FECM model to capture temperature change, oil price shock, and monetary and fiscal policies. So, the model applied here is a little different from (Banerjee et al., 2014) in this regard. The application of such a model is unique in the Indian context.

In the literature, the most popular methods applied for short and long-run forecasting are the models that include the autoregressive and moving average process (ARIMA), Vector autoregression (VAR) and Error-Correction (ECM). These methods rely on a limited number of variables to keep sufficient degrees of freedom for satisfactory inferences. But, the limited variables contain little information. As a result, factor-based time series modelling has gained popularity in economics and finance research during the last one and half decades because of its ability to model data sets of large dimensions and lengths (Stock and Watson, 2002). Dynamic factor models (DFMs) were first proposed by Geweke (1977) as a time-series extension of factor models previously developed for cross-sectional data. The idea behind dynamic factor models is that a few latent factors can accommodate a lot of information across time series.

Factor models effectively synthesise large sets of data, allowing the application of advanced models to the big data (Bai, 2004). More importantly, the dynamics that exist in time-series data must be exploited. The most advanced methods that deal with them are Factor-Augmented VAR (FAVAR) and Factor Augmented Time-Varying Coefficient Regression Model (FA-TVCRM). However, they may not be suitable for forecasting for a medium to long-run period. Because these models do not try to find any stable and long-run relationships among the variables included in the exercise. For this specific reason, Banerjee et al. (2014) recommended the Factor Augment Error Correction model as a better alternative. The present paper attempted to apply this model to Indian quarterly data from 1996Q1 to 2021Q3 for forecasting. We first run the dynamic factor model to reduce 56 macro variables into three factors that capture more than 80% variation. Then, these factors have been included in the error correction model to find a long-run relationship. We find that there exists a long-run relationship. In the model, four exogenous and policy variables have been added. After several permutations and combinations, the best model has been presented. Such relation has been exploited in the forecasting exercise from 2022 to 2035. This model has not been attempted for the Indian economy yet.

The rest of the paper is organised as follows. Section 2 presents a brief review of the existing literature on the factor model. An outline of the methodology applied in the present study has been discussed in Section 3. The main results have been discussed in section 4. And section 5 ends with concluding remarks.

2 Literature

There has been a growing interest to apply the dynamic factor model for the forecasting exercise. Several banks use this framework for the nowcasting of their economies. For example, Bańbura et al. (2013) have done nowcasting for European Central Bank and Bragoli (2017) offered an estimate Japanese economy. The unavailability of a large dataset has very much limited the application of the factor model. Still, in recent years, the researchers have conducted several forecasting studies for the individual and the panel of emerging market economies (EME). Altug and Çakmaklı (2016) did apply this model for Brazil and Turkey. Mandalinci (2017) compared the forecasting performance of various time series specifications for a panel of ten EMEs from the first quarter of 2001 to the third quarter of 2014. For the prediction of inflation and GDP, they modelled univariate and multivariate VAR frameworks along with factor-augmented VARs (FAVAR), time-varying parameter VARs (TVPVAR), and unobserved component stochastic volatility (UCSV) specifications. Overall, the UCSV model outperformed the TVPVAR specification across countries (particularly in Mexico and Turkey). However, during the peak of the global financial crisis, the TVPVAR outperformed others. In the case of India, a time-varying parameter factor-augmented VAR (TFP-FAVAR) performed reasonably well when used in conjunction with the UCSV specification.

In recent years, the dynamic factor method has also become a popular method of nowcasting and forecasting the macro-variable for the Indian economy. So far, most scholars have applied such model to nowcast the Indian GDP. Bragoli and Fosten (2018) nowcasted the GDP of India using the dynamic factor model. However, they stated that nowcasting is more challenging for the Indian economy due to the frequent revisions in GDP data and the limited availability of predictor variables. They constructed a 'pseudo-real-time' historical series from 2007:Q1 to 2014:Q4 and compared the nowcasted GDP data to the final release. A set of international series has been added, and that seems to have improved the nowcasts of Indian GDP markedly during the global crisis period in 2008-09. Iyer and Gupta (2019a) nowcasted GDP growth for quarters using a dynamic factor model (DFM) estimated from January 2000 to December 2018 with the help of 18 variables, including environmental factors like rainfall. The quarterly variables include a Business Confidence Index and the components of GDP calculated using the expenditure approach. They compared the nowcasts generated by the DFM with the predictions of AR models. The DFM outperformed the other competing models. A key finding is that rainfall has high predictive content for economic growth.

Yadav (2021) nowcasted the Indian GDP in real-time using the factor bridge and factor VAR model. This study is the first research work that used a real-time dataset for both the dependent and independent variables for nowcasting Indian GDP. The real-time datasets have issues of data revision and biases, which have been handled using the factor modelling approach along with the bridge model and vector autoregression model. The nowcasting performance is evaluated with the benchmark model and the survey of professional forecasters by RBI in real-time. Nowcasting models also assessed the impact of information flow within a quarter by nowcasting quarterly GDP growth rate at the end of each successive month. The month-on-month performance of all models has shown improvement and confirms using the real-time information and recursive nowcasting at every month-end. The VAR model with principal components has outperformed the professional forecaster and benchmark model survey.

Bhadury et al. (2020) constructed a Coincident Economic Indicator for India (CEII), almost similar to the DFM, using a sequentially expanding list of high-frequency indicators into a couple of groups. The indicators used in different blocks represent various sectors, display high contemporaneous correlation with GDP, and track GDP turning points. In the emerging economies, including India, GDP dynamics is seen to be more volatile, displaying significant accelerations and decelerations in growth in quick succession. Therefore, a desirable feature indicator selection would capture such a dynamic. This study adopted the forward step-wise selection procedure, the lasso selection procedure, to achieve this. After selecting the relevant variables, estimated a single factor representing the common trend underlying these variables. The single factor is obtained by calculating a dynamic factor model (DFM). For analytical clarity, they have sequentially estimated 6-indicators, 9-indicators and 12-indicators. Accordingly, they examined the out-of-sample performance of the nowcasting models during 2017Q1-2019Q1. They observed that the out-of-sample performance, measured in a root mean squared error (RMSE), is better for the CEII-6 than the CEII-9 and CEII-12 models. Further, The jagged-edge and mixed data sampling (MIDAS) regression are also used to exploit the rich information contained in the monthly DFs to nowcast quarterly GDP and improve out-of-sample performance.

Bhattacharya et al. (2021) used the Factor Augmented Time-Varying Coefficient Regression Model for nowcasting the quarterly GDP growth of India with the information for the period 2004-05: Q1 to 2020-21:Q4. The model has been estimated separately for two separate periods: Specification I for 2007-08:Q1 to 2019-20:Q3 using only 19 indicators and Specification II for the period 2015-16:Q1 to 2019-20:Q3 that includes a larger set of 28 indicators. Moreover, they have compared two alternative models and found that the model outperformed the DFM model in terms of both in-sample and out-of-sample root mean square error (RMSE). Within the sample period, the RMSE of the ARIMA model is slightly lower than that of the FA-TVCR model, but it is higher than that of the FA-TVCR model outside of the sample period. Furthermore, they used the Diebold-Mariano test to compare the three models' predictive power and revealed that the FA-TVCR model consistently outperformed the DFM model. The FA-TVC and the ARIMA models are equally accurate in the out-of-sample forecast.

Bhattacharya et al. (2021) projected the path of the Indian economy over the next four years (2021-22 to 2024-25, using the standard regression techniques based on the data spanning from 1991 to 2019. The empirical approach followed by Bhattacharya et al. (2019) and Iyer and Gupta (2019b) has been utilized in this study. The study includes GDP growth globally (excluding India) as an exogenous variable in the forecasting model to project the Indian GDP growth rate in light of the projected future for the other countries. They also implicitly include the working-age population growth, education, the rule of law, technology, and openness to trade and finance in the model by an autoregressive term and trend term. The dummy variable for 2009 captures the global financial crisis period. The results show that India's economic growth variation is substantially dependent on global economic developments. During the projection window 2021-22 to 2024-25, the global economy is forecasted to rebound strongly in 2021 and gradually return to growth of around 3% per annum. The Indian working-age population growth is projected to decrease from 1.4% to 1.1% per annum. The projection of this study further compared with the IMF projection (April 2021 WEO) and alternative model and found consistent findings. It is projected that after the pandemic, GDP growth will rebound at the end of the year and then slide towards 6-7% in the medium term. This projection implies that, after the ongoing pandemic subsides, India would continue to catch up to the level of economic welfare in the developed world faster than almost any other large emerging market economy. Qian (2018) nowcasted the Indian GDP using the dynamic factor model and Kalman filter. This paper incorporates two primary data sources, the traditional data sources, typically used in economic forecasting applications and the aggregated Google Search data, spanning the 2000M1 to 2017M08 period. This study selected those series used by Bragoli and Fosten (2018) to forecast Indian GDP growth. The model is estimated using an expectation-maximization algorithm of Giannone et al. (2008) to deal with the missing data. The results reveal that incorporating search data into the prediction procedure provides no improvement over the baseline model. However, including a multifactor setup appears to improve forecasts.

Conclusively, it is observed that most of the existing studies on the Indian economy are confined to applying DFM to nowcast the macro-variables for a limited period using incomplete and noisy data. They confined to forecast the short-run dynamics and did not deal with exogenous shocks and innovations.

3 Methodology

The approach applied here is heavily influenced by the availability of big data and their stationarity levels. We use the Factor-augmented Error Correction Model (FECM). First, the level of stationarity has been checked for all the variables. Second, the dynamic factor model has been employed to extract the factors taken into the error correction model to find a long-run relationship. This method is different and an improvement from the standard ECM and VECM (Banerjee and Marcellino, 2009; Banerjee et al., 2014). It protects from the omitted variables biases and the dependence of cointegrating relations among a limited set of variables. This approach is also far improved from applying standard dynamic factor models, which do not include the error correction terms into the equations for the critical variables under analysis. The inclusion of ECM prevents errors from being non-invertible MA processes. In other words, this model is somewhat a combination of ECM and FAVAR. On top of this, a few policy variables that change exogenously over time have been added to the model.

Let us specify the model here. Assume that the N number of $I(1)$ variables x_t evolve according to the $VAR(p)$ model as follows:

$$x_t = \pi_1 x_{t-1} + ... + \pi_p x_{t-p} + \epsilon_1 \tag{1}$$

where ϵ_t is i.i.d $(0, \Omega)$. The initial values can be assumed fixed and set equal to zero for simplicity.

Now, the $VAR(p)$ can be further parameterised into the form of either Error Correction Model (ECM) or the so-called common factor trend specification. The form of ECM can be written as below:

$$\Delta x_t = \alpha\beta' x_{t-1} + v_t \tag{2}$$

where, $\Pi = \sum_{s=1}^{p} \Pi_s - I_N = \alpha_{N\times N-r}\beta'_{N-r\times N'}$

$v_t = \Gamma_1 \Delta x_{t-1} + ... + \Gamma_{p-1}\Delta x_{t-p+1} + \epsilon_1$

$\Gamma_i = -\sum_{s=i+1}^{p} \Pi_s$

$\Gamma = I_N - \sum_{i=1}^{p-1} \Gamma_i$.

It is further assumed that the large set of variables, x_t can be presented into a few common factors. And, the common factor trend specification can represented as:

$$x_t = \Psi f_t + u_t \tag{3}$$

where,

$\Psi_{N\times r} = \beta_\perp(\alpha'_\perp \Gamma \beta_\perp)^{-1}$

$f_{t_{r\times 1}} = \alpha_\perp \sum_{s=1}^{t} \epsilon_s$

$u_t = C(L)\epsilon_t$.

β': $N - r \times N$ matrix of cointegrating vectors with rank $N - r$

α: loading matrix

$N - r$: Number of co-integrating vectors

r: the number of $I(1)$ common stochastic trends, where $0 < r \leq N$

u_t: N-dimensional vector of stationary errors.

We assume that the linear combination of variables at first difference are not correlated with lower order of common factors. See Johansen et al. (1995) and Banerjee and Marcellino (2009) for the derivations and better understanding of the model exposition.

Let us separate out GDP (real term in logarithmic form) from x. Again, f_t are the factors that capture more than 80% of variations within x_t. It may be seen that GDP_t and f_t are cointegrated, while the f_t are uncorrelated with random walks. Further, assume that Z_t is a vector of I(0) variables representing exogenous shifts and policy dimensions. Then, the Factor-augmented Error Correction Model (FECM) can be represented as follows:

$$\begin{pmatrix} \Delta GDPt \\ \Delta f_t \end{pmatrix} = \begin{pmatrix} \gamma_G \\ \gamma_f \end{pmatrix} \delta' \begin{pmatrix} GDP_{t-1} \\ f_{t-1} \end{pmatrix} + A_1 \begin{pmatrix} \Delta GDP_{t-1} \\ \Delta f_{t-1} \end{pmatrix} + ... + A_q \begin{pmatrix} \Delta GDP_{t-q} \\ \Delta f_{t-q} \end{pmatrix}$$
$$BZ_t + \begin{pmatrix} \epsilon_{Gt} \\ \epsilon_t \end{pmatrix} \quad (4)$$

Where, for k number of $I(0)$ variables, B represents the dimension, $(r+1), k$. The fitted results of this model have been applied for the forecasting exercise. At first, the model produces in-sample observations, and the RMSE between the actual and forecasted values shows the performance of the model. Once it passes satisfactory criteria, the model has been applied for the out-sample forecasting.

For out-sample forecasting, two alternative techniques have been applied to evaluate the benefit of using the dynamic factor model. First, we apply an automatic ARIMA forecasting model. This method executes forecasting values for a single series based upon an ARIMA model. It tries to find the best-fit version from the alternative combination of AR and MA processes built on its lags and disturbance terms. Needless to say, this did not include the effect of any other factors in the process. So, the forecasting found from this process shows a path based on own dynamics experienced in the past. The automatic ARIMA method have been applied for projecting exogeneous variables.

Second, the estimated FECM model could be used to forecast the series of endogenous variables simultaneously. The h-step ahead,$\tau + h + x_{1,\tau} = T - h - t, ..., T - h$,and constructed as:

$$\hat{x}^h_{1,\tau+h} = x_{1,\tau} \sum_{i=1}^{h} \Delta \hat{x}_{1,\tau+i}, \tau = T - h - t, ..., T - h \quad (5)$$

The forecasting performance has been evaluated with Root Mean Square Errors (RMSE) applied on the in-sample observations. The MSE is given by

$$\mathrm{MSE}_h = \frac{1}{N}\sum_{t=1}^{N}(x^h_{T-N+j} - \hat{x}^h_{1,T-N+j}) \tag{6}$$

Therefore, this model first reduces the dimensionality of large datasets for use in econometric analysis by extracting dynamic factors. Then, these factors are applied in the error correction model to establish a long-run relationship. So, the GDP and factors explaining 80% of the total variations of all the variables have been included in the error correction model and VECM estimation. The dynamics of short and long-run relationships will be exploited for the forecasting in the presence of a few exogenous variables. Note that the I(0) variables that may capture macro policies have been included in the model as exogenous. In this case, the exogenous variables have been predicted using the automatic ARIMA model for the forecasting of out-sample observations for the endogenous variables.

4 Database

Our attempt here is to forecast the Indian GDP that reasonably reflects the business cycle in the medium to the long-run horizon using high-frequency quarterly indicators. The GDP data were obtained from the Central Statistical Organization, Ministry of Statistics and Programme Implementation (CSO, MOSPI). The rest of the variables are mainly drawn from RBI, CMIE, the World Bank, and the India Stat database. The variables available on monthly frequencies have been converted to a quarterly format. We considered them block-wise. Due to missing observations for several variables, We have managed to find 56 variables in our dataset for the entire period, 1996Q1 to 2021Q3, divided into ten blocks. The blocks are prices, money banking and interest rates, public finance, external, energy, income/consumption, industry, investment, capital market, and climate. The variables included in each block and their sources and frequencies have been presented in Table A1 (see Appendix).

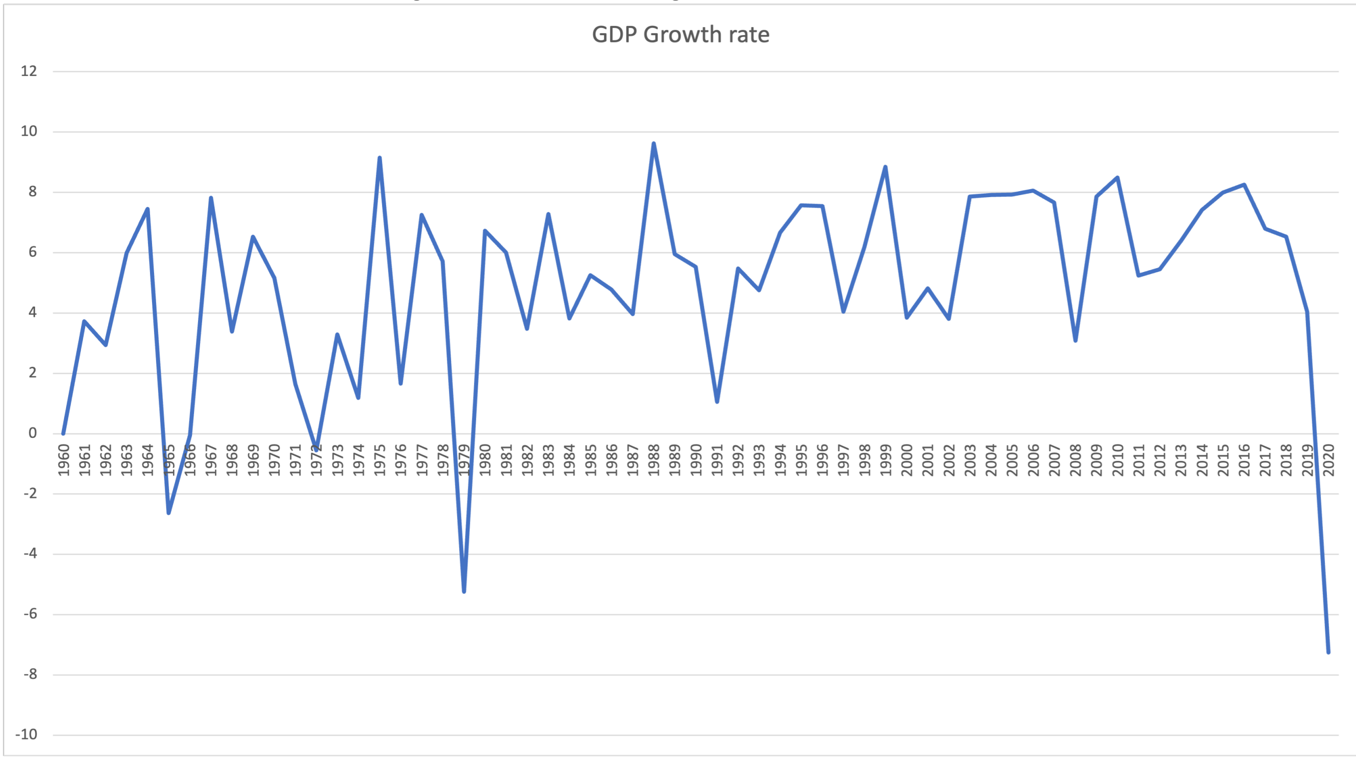
5 Empirical Results and Discussion

5.1 Growth rate dynamics

Before forecasting the growth rate, let us first discuss the long-run dynamics of GDP in the real term. India's GDP growth rate accelerated from 3.5% in the 1970s to 5.5% in the 1980s. The decline in growth in the 1970s was reversed in the mid-1980s, mainly due to implementing several industrial reform initiatives to improve domestic competitiveness. Since the early 1990s, growth impulses have appeared to have gained more traction due to broad-based reforms affecting all sectors of the economy. In the latter half of the 1990s, there was some slackening in the pace of structural reforms, which coincided with the onset of the East Asian financial crisis, setbacks in the fiscal correction process, quality of fiscal adjustment, the slowdown in agriculture growth due to lower-than-normal monsoon years. Based on the data of world development indicators, the GDP of India registered an annual average growth rate of 6.6% in real terms in the 1990s (see Figure 1). The growth rate slowed in 2011 to 5.25% and gradually increased to 8.26%. From 2016 growth slowed down to 4.04% in 2019. With the Covid pandemic and stringent lockdown, the growth turned negative, minus 8% in 2020, with revision in 2021. Given these growth rate dynamics, we are interested in predicting the long-run trend.

However, the economy maintained a steady growth rate of more than 8% during the early 2000s. After that, the rate has slowed down and fluctuated from the late 2000s to recent years for various reasons. The global financial crisis triggered the slowdown. The continual poor growth performance of the development world, structural and tax reforms undertaken by the government, oil price rise and lately the COVID Pandemic added to the declining forces and could not let the growth achieve the potential level. Under normal circumstances, one would predict to grow at 8-10% in the recovery phase. Let us see how it is achievable counting some policy and external shocks.

Figure 1: Real GDP growth rate



Notes :Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2015 prices, expressed in U.S. dollars.

Source: World Bank

5.2 Stationarity Tests

At first, all the variables were run through a stationarity test. The ADF method has been used for checking the stationarity of the series. The ADF regression used to obtain the test statistic includes a constant term and time trend. In the last column of Table A1, we have specified the order of integration of series. The stationarity level of all the variables has been presented in Table 1. Only the $I(1)$ variables have been used in the factor estimation.

5.3 Dynamic Factors Estimation

The I(1) variables have been taken for the dynamic factor extraction. Factor loadings, or the correlation of each indicator with the calculated latent factors, are reported in Table A2. The factor loadings give the variance explained by the data linked with each factor. In our analysis, the factors that explained up to 80% of variation have been included. We find that the first three factors explained more than 80% variation. In other words, these three factors in the regression analysis can do the same job of 56 variables. Note that the first factor, denoted by F1 in Table A2, shows Finished steel, broad money, bank credit, cash in circulation, cargo handled at ports, exchange rate, M3, non-food credit and tourist arrival contribute to a greater extent. Similarly, factor F2 is highly influenced by the foreign exchange turnover purchase, import, CPI Industrial workers, rainfall sale of commercial vehicles etc. The factor F3 extracts variations from BSE, car sales, gas production, IIP manufacturing etc. We have several dynamic factor estimates that capture industrial advancements and technological progress. Hence, the model has not included a separate technology or productivity variable. These three factors will be treated as variables with their time-series properties and applied in the regression analysis.

5.4 Co-integration Results

The VAR model includes the GDP (in real term) and three factors. The test statistics found for lag selection criteria suggests that the number of lag to be considered in the model should be four (see Append A3). Before running the forecasting model, we need to find whether there has been any long-run co-integration between the factors and the GDP. The GDP is the variable of our interest. To find the number of the co-integrating equation, we estimated s Johansen's trace statistic. The trace statistics of co-integration result indicates that the model must have one co-integration relation (see Append A4). It means that one should include error correction terms to apply FECM or error correction model with factors in the regression that can offer a better prediction for long-run forecasting. So, we need to run an error correction model with the estimated factors.

5.5 Exogenous Variables

In the long-run forecasting, one needs to include the policy and external shocks assumed to influence the economic dynamics. We have considered four exogenous and policy variables to capture four sets of macro instruments. Two of them represent innovations aiming at fiscal and monetary policies. The other two are external shocks.

(1) Reserve Bank of India has already declared to introduce the digital currency soon (Bhowmik et al., 2022). The scholars have been trying to understand its impact on the economy. Undoubtedly, the introduction of digital currency would further reduce the demand for holding cash. This objective may be reflected in the Cash-reserve ratio (CRR), which would serve as an expansionary strategy. CRR is one of the monetary policy

instruments. The approach undertaken by the central bank to monitor the transmission of mechanisms has changed and evolved regarding the monetary policy instruments. In May 2016, India implemented Flexible Inflation Targeting. The aim was to reduce cash transactions, which could smoothen the transmission mechanism of monetary policies. The introduction of digital currency seems to be one ahead in this direction. So, CRR has been one of the exogenous variables.

(2) While increasing government expenditure plays a multiplier effect in the economy, the actual impact is limited by the effective delivery of projects and money disbursement. The government has planned to govern all activities through e-governance under the Digital India programme to reduce all types of inefficiencies (denoted as PM Gati Sakti). So, the public expenditure on the completed project out of GDP (*comp_gdp*) captures the efficacy of fiscal policy due to digitalisation and institutional reforms. The actual spending on the public sector may differ from the planned expenditure. That's why the spending on completed projects has been considered to be an institutional variable serving as an expansionary fiscal policy. If the institutional efficacy improves, one can argue that the share of the completed project would accelerate.

(3) The price of crude oil (denoted as crudeoil) has been included to capture external shocks. The oil price is determined in the international market, and India is an oil-importing country. The national economy has little influence on it. A rise in global oil prices pushes inflationary pressure in the economy. In a recent study, Ghosh and Tomar (2019) found that a crude price shock increases the CAD to GDP ratio even if GDP growth increases. In a scenario of a 10 USD/barrel increase in oil price and absorption of the entire price shock by the government rather than pushing it to the consumers, inflation as a percentage of GDP is expected to increase by roughly 49 basis points (bps) and fiscal deficit as a percentage of GDP by 43 bps.

(4) The temperature (temp) has been taken to include climatic change. The global temperature is rising, essentially affecting agriculture and associated economic activities. According to Handa (2020), the temperature rise in India has adversely affected the economic growth by 0.5-1.5%. Recent studies have highlighted the impact of an increase in global average temperature shock on GDP in India. Recently published data suggests that the average temperature across India has increased by 0.62°C over the last 100 years (Government of India, 2021). Some studies tried to estimate the impact of the increase in the average temperature on the gross domestic product (GDP) in India by 2100. It has been observed that the districts in India that have warmed at a faster rate have seen 56% less growth in the gross domestic product (GDP) compared to the slowly warmed districts

Burke and Tanutama (2019). Similarly, if the global average temperature increases by 2°C, India's GDP is projected to decline by 2.6% based on the impact of temperature and precipitation changes on labour productivity in different sectors of the economy. However, in an alternative scenario of 4°C declines in global average temperature, the decrease in GDP is estimated to be around 13% Kahn et al. (2021). The above studies have considered only the direct impact of increasing temperature on labour productivity and GDP. However, there may be indirect impacts on labour productivity through increased incidence of endemic vector-borne diseases Dhiman et al. (2010). (Kompas et al., 2018) based on a decline in agricultural productivity, sea-level rise and health expenditure, estimates. While a 1°C increase in average global temperature is expected to decline India's GDP by 3% per annum, a 3°C increase in average global temperature is expected to decline GDP in India by 10% per year. Hence, the average temperature is taken as another exogenous variable. These four variables are stationary at $I(0)$ and have not been included in the factor estimation.

5.6 Forecasting Results

5.6.1 Pre-estimation Diagnostic

In the error correction model, we need to include exogenous variables and the three factors that capture 80% variations among all the variables. The result factor error correction model has been presented in Table A5. Note that the model passed the diagnostic test reasonably well. The coefficient of error correction term appears to be negative and statistically significant. So, we may infer that the model would produce a stable long-run relation once it hits by a shock. Moreover, while the first and third factors contribute to the GDP favourably, the second factor depends a bit. Though, the dampening factor is not statistically significant.

Once we look at the short-run dynamics, it shows that the change in GDP is significantly influenced by the lag difference up to the fourth period. While the coefficients of the first three lags are affected negatively, the fourth lag difference contributes to the change. This sort of result justifies the seasonality of the GDP. Moreover, the first difference of all three factors has become statistically significant. The coefficients of temperature (TEMP) and cash reserve ratio (CRR) is found negative and significant. This result suggests that the rise of temperature and the crude oil price adversely affect economic growth. The impact of oil prices is relatively stronger than others. A $10 rise of oil price would dampen the growth rate by approximately 0.37%. But, the coefficient of investment in the completed project (COMP-GDP) shows significant and positive figures, meaning that an improvement of effective delivery of government projects boosts economic growth. Similarly, a coefficient of CRR becomes negative, meaning that a drop of CRR that serves as an expansionary monetary policy seems to boost economic growth.

5.6.2 Results and Post-estimation Diagnostic

In order to forecast the GDP (the variable of our interest), we should have prior information on all the exogenous variables. Instead of inflating them arbitrarily, automatic ARIMA forecasting has been applied to generate the series from 2022 to 2035. The method is superior to others as it tried to predict using the best-fitted model out of all possible AR and MA series of the variables and its disturbance terms. The predicted series of all the four exogenous variables have been presented in Figure 2. Note that government investment seems to show a rise with substantial seasonal fluctuations due to institutional reforms undertaken with the help of e-governance. Similarly, the cash-reserve ratio has declined significantly and is expected to drop further once the digital currency is introduced. This could play an expansionary role in the economy. However, it cannot exhaust the demand for holding cash entirely. Our estimate suggests that the CRR would drop from 4% in 2021 to around 2% in 2035.

On the other hand, the price of crude oil is expected to rise, and this seems to have a regressive impact on the growth. The automatic ARIMA predicts that oil price may gradually rise upto US$ 140 per barrel. According to the balance, a web-based news magazine, The US Energy Information Administration (EIA) predicts that by 2040, prices are projected to be $132 per barrel. The cheap oil sources will have been exhausted by then, making it more expensive to extract oil. By 2050, oil prices could be $185 per barrel. West Texas Intermediate (WTI) per barrel price is expected to rise to $128 by 2040, and $178 by 2050 (Source: https://www.thebalance.com/oil-price-forecast-3306219). Similarly, the temperature is also expected to increase gradually with its quarterly fluctuation. According to BBC news, at the current rate of warming - 0.2C per decade - global warming will reach 1.5C between 2030 and 2052 (Source: https://www.bbc.com/news/newsbeat-48947573). Our estimate accounted for a marginal rise of temperature at the same rate.

We have also forecasted GDP series using the same methodology (see Figure 3) for reference. Note that the series take actual observations upto the point of data availability (2021Q3 for our case). Suppose the predicted series of exogenous variables are fit into the estimated FECM model. One can generate a series of GDP forecasts. Quarterly forecasted values have been presented in Figure 3 (see the orange line). Note that the in-sample forecasting also strictly follows actual GDP fluctuation, except in the recent past. The in-sample forecasting evaluation statistics suggest that the model has been significant enough to predict the series. We find that RMSE and Theil U1 account for 0.04 and 0.002, respectively. It demonstrates the marginal difference between the actual and predicted series. Moreover, the F-statistic of forecast evaluation is statistically significant. Therefore, this model can be applied to generate out-sample forecasting.

The forecasted quarterly values of GDP (in the logarithmic term at constant price) have been shown in Figure 3. Note that the FECM predicted value is lower than the ARIMA forecasted series. It is because the ARIMA forecasted series did not take account of long-run relation with the factors and exogenous policy and external shocks. While the rise of government investment is expected to boost the growth, the increase in oil price and temperature would dampen the growth. Taking all those forces, we find that the annual growth rate would be limited to 4-5% in the long run during 2022-35. Of course, the institutional reform and introduction of digital currency, playing favourable fiscal and monetary policies, would add to the growth acceleration. But, there is little scope for CRR to fall as it is already very low. Moreover, the national government has already targeted to limit the fiscal deficit to 3.3% in the near future. As a result, the fiscal expenditure cannot grow fast to accelerate the growth. But, through institutional reform and digitalisation, the efficiency of public spending is expected to boost economic growth to a certain extent. The factors that would seriously dampen the economic growth seem to be the rise of oil prices and temperature. If the government aims to double the growth rate, the oil price needs to be kept low, and the temperature should not rise. One may argue that the oil price rising from around \$80 per barrel to \$140 per barrel by 2035 looks like a significant jump. If the price can be kept around \$100 per barrel, the growth rate can be gained by roughly 1.5% (see the regression coefficient in the FECM model). No further rise of temperature and oil prices may raise the growth rate closer to 8%. So, the predicted growth can range between 4-8% during one and half decades, depending upon the extent of temperature and oil price rises.

Figure 2: Forecasting exogenous variables with automatic ARIMA method

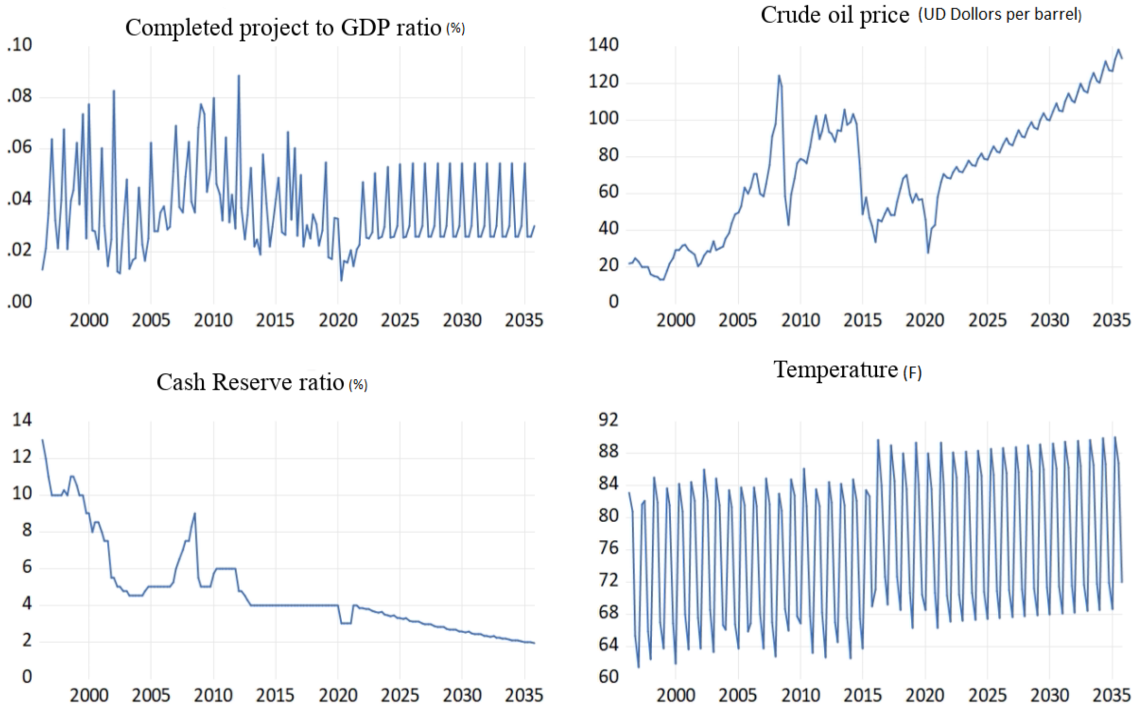


Figure 3: Quarterly Forecasting GDP (Constant Prices in logarithmic term)

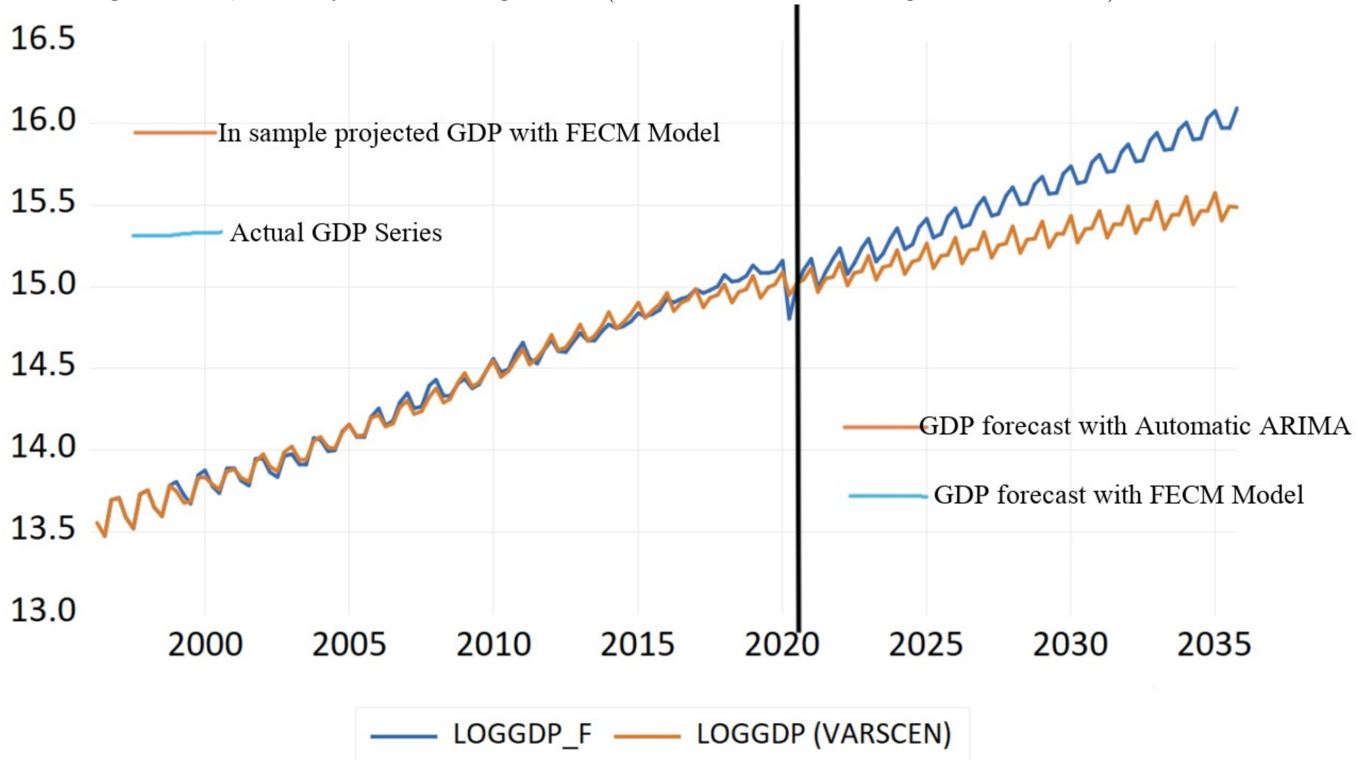
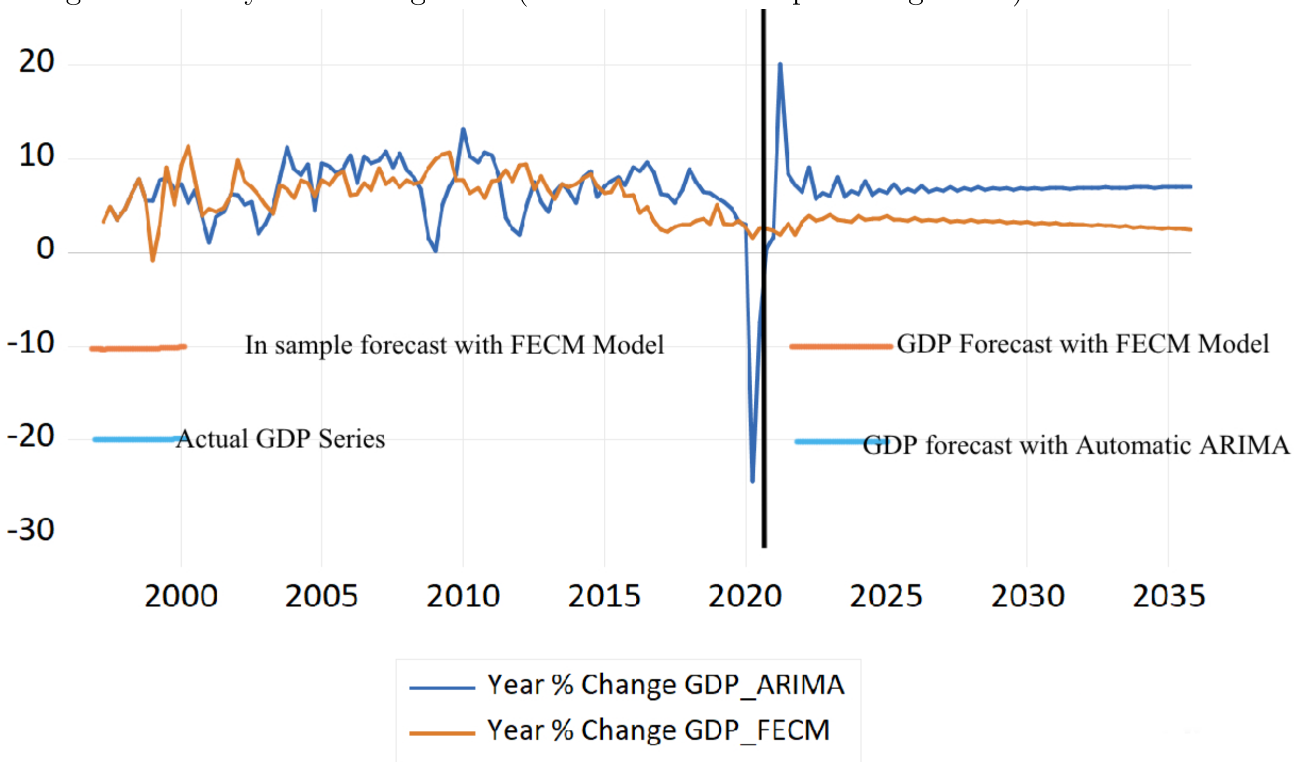


Figure 4: Yearly Forecasting GDP (Constant Prices in percentage term)



6 Concluding Observations

The paper attempts to estimate the long-run forecasting of the Indian economy for the post-COVID period. The FECM has been applied for this purpose. Since this model extracts information from big data of many variables and reduces it into a few dimensions (factors), using such factors in the prediction is expected to show better results. We gathered quarterly data for 56 variables from 1996Q1 to 2021 Q3. Dynamic factor model has been applied on these variables that produce three factors capturing 80% of the total variation. These three factors, along with four exogenous variables of $I(0)$ series, have been considered in running the FECM model that produced satisfactory results of in-sample forecasting. The exogenous variables have been augmented using the automatic ARIMA model. The results of out-sample GDP forecasting show that the economy would grow at 4-5% growth rate in the next one and half decades. The growth rate produced by the FECM model seems to be lower than that of the automatic ARIMA model. Because, the FECM has been able to capture the dynamics of factors and exogenous variables. The rise of temperature and oil price is expected to dampen the favourable effect of expansionary fiscal and monetary policies to be expected from the prescribed institutional reforms, e-governance and digital currency. The resultant forces seem to show lower growth than the ARIMA model. The government should find strategies to deal with rising oil prices and temperature to accelerate economic growth. If the oil price and temperature can be kept to the current level, the growth rate can go closer to 8%.

Compliance with Ethical Standards

D Maiti was asked by EGROW Foundation in association with Niti Aayog to prepare a draft on Indian long-run forecasting and presented at the Workshop organised by them on 9-9th March 2022 and National Conference on 12-13th March 2022 organised by Bengal Economic Association. He jointly worked with N Kumar, D Jha and S Sarkar. We confirm that all have contributed equally and do not have any conflict of interest.

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Appendix

Table 1: Variables and Stationarity level

Block Name	Block	Series ID	Series	Frequency	Stationarity
	0	GDP-CUP	Gross domestic product at current market prices	q	I(1)
	1	IW-GI	Industrial workers-General index	q	I(2)
	1	AL-GI	Agricultural labourers-General index	q	I(2)
	1	RL-GI	Rural labourers-General index	q	I(2)
	1	WPI	Wholesale price index (spliced series)	q	I(2)
Prices	1	WPI-PA	Primary articles	q	I(2)
	1	WPI-FP	Fuel power	q	I(2)
	1	WPI-M	Manufactured products	q	I(2)
	1	crudeoilprice	Crude Oil Price	q	I(1)
	1	gold	Gold Price (INR per 10gms)	q	I(1)
	1	HPI	House Price Index : All India	q	I(1)
	2	M3	Money supply (M3)	q	I(0)
	2	sensex	Sensex Close	q	I(1)
	2	circulation	Currency in circulation (INR Crore)	q	I(1)
	2	broad	Broad money (INR Crore)	q	I(1)
	2	reserve	Reserve money (INR crore)	q	I(1)
Money , Banking and Interest Rate	2	Aggdeposit	Aggregate deposit	q	I(1)
	2	Bankcredit	Bank credit	q	I(1)
	2	Nonfoodcredit	Non-food credit	q	I(1)
	2	CRR	Cash reserve ratio (CRR) (March-end)	q	I(0)
	2	SLR	Statutory liquidity ratio (SLR) (March-end)	q	I(1)
	2	BANKRATE	Bank rate (March-end)	q	I(1)
	3	Taxreceipt	Tax receipt	q	I(1)
	3	govexpenditure	Central government expenditure	q	I(1)
	3	Planexp	Plan expenditure	q	I(1)
	3	Nonplanexp	Non-plan expenditure	q	I(1)
Public Finance	3	Interest	Interest	q	I(1)
	3	Revenue expenditure	Revenue expenditure	q	I(1)
	3	Capital expenditure	Capital expenditure	q	I(1)
	3	Revdeficit	Revenue deficit	q	I(1)
	3	fiscaldeficit	Gross fiscal deficit (GFD)	q	I(1)

	4	Exports	Exports	q	I(1)
	4	POL	POL	q	I(1)
	4	Non-POL	Non-POL	q	I(1)
	4	Exp-POL-Readymade	Readymade garments (RMG) of cotton including accessories	q	I(1)
	4	Exp-POL-Motor vehicle/cars	Motor vehicle/cars	q	I(1)
	4	Imports	Imports	q	I(1)
	4	POL	POL	q	I(1)
	4	Non-POL	Non-POL	q	I(1)
	4	IMP-Gold silver	Gold silver	q	I(1)
	4	IMP-Gold	Gold	q	I(1)
	4	IMP-Silver	Silver	q	I(1)
	4	IMP-Non-Pol non-gold	Non-Pol non-gold silver	q	I(1)
External	4	IMP-Pearls, precious and semi-precious stones	Pearls, precious and semi-precious stones	q	I(1)
	4	IMP-Telecom instruments	Telecom instruments	q	I(1)
	4	IMP-Coal, cokebriquettes	Coal, coke briquettes	q	I(1)
	4	IMP-Iron steel	Iron steel	q	I(1)
	4	IMP-Vegetable oils	Vegetable oils	q	I(1)
	4	Trade balance: DGCIS	Trade balance: DGCIS	q	I(1)
	4	Tourist arrivals	Tourist arrivals	q	I(1)
	4	Total foreign exchange reserves	Total foreign exchange reserves	q	I(1)
	4	fii	Foreign Institutional investement	q	I(1)
	4	Foreign currency assets	Foreign currency assets	q	I(1)
	4	euroleading	Euroleading Indicators	q	I(1)
	4	neer	Net Effective exchange rate	q	I(1)
	4	Exchange rate	Exchange rate	q	I(1)
	5	Crude oil production	Crude oil production	q	I(1)
	5	Coal production (excluding lignite)	Coal production (excluding lignite)	q	I(1)
	5	Coal imports	Coal imports	q	I(1)
	5	Power capacity	Power capacity	q	I(1)
Energy	5	Electricity generation (Utiltiies)	Electricity generation (Utiltiies)	q	I(1)
	5	Hydel	Hydel	q	I(1)
	5	Thermal	Thermal	q	I(1)
	5	Nuclear	Nuclear	q	I(1)
	5	Natural gas gross production	Natural gas gross production	q	I(1)
	6	Railways: freight traffic	Railways: freight traffic	q	I(1)
	6	Cargo handled at major ports	Cargo handled at major ports	q	I(1)

Income/consumption

	6	petconsump	Consumption Of Petroleum Products	q	I(1)
	6	Car sales	CAR sales	q	I(1)
	6	Tractors sales	Tractors sales	q	I(1)
	6	consumption	Private Final Consumption Expenditure (INR)	q	I(1)
	7	manuf	IIP-Manufacturing	q	I(1)
	7	iip	Index of industrial production (IIP)	q	I(1)
	7	minequar	IIP-Mining quarrying	q	I(1)
Industry	7	elec	IIP-Electricity	q	I(1)
	7	Two-wheelers sales	Two-wheelers sales	q	I(1)
	7	Commercial vehicle sales	Commercial vehicle sales	q	I(1)
	7	Finished steel (alloy non-alloy) production	Finished steel production	q	I(1)
	8	New projects	New projects	q	I(1)
	8	Completed projects	Completed projects	q	I(1)
Investment	8	Stalled projects	Stalled projects	q	I(1)
	8	Investment projects, outstanding	Investment projects, outstanding	q	I(1)
	8	IVT-OU	Investment project Under implementation	q	I(1)
	9	bse	Turnover BSE	q	I(1)
	9	nse	Turnover NSE	q	I(1)
	9	gfcf	Gross Fixed Capital Formation	q	I(1)
	9	Capital issues	Capital issues	q	I(1)
Capital market	9	Equity	Equity	q	I(1)
	9	Debt	Debt	q	I(1)
	9	Number of companies listed	Number of companies listed	q	I(1)
	9	Market capitalisation all listed companies	Market capitalisation all listed companies	q	I(1)
	9	Trading volumes on Bombay Stock Exchange (BSE)	Trading volumes on Bombay Stock Exchange (BSE)	q	I(1)
	9	Trading volumes on National Stock Exchange (NSE)	Trading volumes on National Stock Exchange (NSE)	q	I(1)
Climate/Environmet	10	rainfall	Rainfall All India	q	I(1)
	10	temp	All india average temperature	q	I(1)

Table A.2: Estimated Factors and Loadings

VARIABLE	Fl	F2	F3
Agricultural labourers-General index	0.925	0.363	0.040
FINISHED STEEL	0.862	0.324	0.304
BANK CREDIT	0.941	0.336	-0.001
BROAD MONEY	0.942	0.335	-0.015
TURNOVER BSE	0.227	0.041	0.529
CAPITAL ISSUES	0.914	0.178	-0.032
CAR SALES	0.738	0.360	0.492
CARGO HANDLED AT MAJOR PORTS	0.830	0.357	0.387
CIRCULATION	0.922	0.363	-0.031
COAL IMPORT	0.910	0.322	0.033
COMMERCIAL VEHICLE SALES	0.748	0.306	0.456
COMPLETED PROJECT	0.778	0.079	0.294
DEBT	0.915	0.169	-0.056
AGGREGATE DEPOSIT	0.944	0.330	-0.011
ELECTRICTY GENERATIONS	0.915	0.351	0.146
EUROLEADING INDICATORS	-0.240	-0.274	0.063
RESERVE MONEY	0.851	0.397	0.272
EXCHANGE RATE	0.906	0.256	-0.130
FOREIGN EXCHANGE RESERVE	0.924	0.357	0.055
FETPURCHASE	0.766	0.421	0.408
FET SALES	0.773	0.417	0.406
FOREIGN CURRENCY ASSET	0.851	0.386	0.271
GAS PRODUCTION	0.121	0.340	0.655
GOLD IMPORT	0.874	0.409	0.084
HYDDEL POWER	0.351	0.665	0.026
IIP GENERAL INDEX	0.883	0.370	0.259
LOGIMPORT	0.777	0.432	0.442
INV PROJECT UNDER IMPLEMENTATION	0.901	0.383	0.114
INSTALLED PROJECT	0.585	0.125	0.266
INVESTMENT OUTSANDING PROJECT	0.871	0.402	0.220
LOGCONSUMPTION	0.885	0.359	0.271
LOGEXPORT	0.804	0.408	0.414
LOGGFCF	0.834	0.392	0.381
M3	0.943	0.331	-0.013
IIP MANUFCTURING	0.872	0.381	0.270
IIP MINEQUAR	0.887	0.259	0.293
NO COMPANY LISTED	-0.098	-0.237	-0.501
NONFOOD CREDIT	0.942	0.335	-0.004
NSE TURNOVER	0.873	0.281	-0.085
WPI -FUEL POWER	-0.195	0.045	0.178
CPI-INDUSTRIAL WORKER	0.057	0.881	-0.014
WPI MANUFACTURED PRODUCT	0.871	0.407	0.251
WPI -PRIMARY ARTICLE	0.889	0.412	0.117
CPI- RURAL LABOURER- D	-3.99	1.00	-3.071
POWER CAPACITY	0.948	0.292	0.006
RAILWAY FRIEGHT	0.871	0.341	0.337
RAINFALL	-0.186	0.464	-0.185
SENSEX	0.909	0.357	0.081
THERMAL	0.897	0.259	0.235
FOREIGN TOURIST ARRIVAL	0.808	0.207	0.284
TRACTOR SALES	0.838	0.405	0.121
TWO WHEELER SALES	0.845	0.367	0.230
BSE TRADING VOLUME	0.237	0.049	0.522
NSE TRADING VOLUME	0.873	0.284	-0.088
WPI-D	0.138	0.205	0.167
RESERVE	0.925	0.364	0.003
SLR	-0.834	-0.245	0.011

Table A.3: Lag Length

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-235.175	NA	0.002	5.199	5.309	5.244
1	251.650	920.737	7.640	-5.036	-4.488	4.815
2	280.593	52.223	5.780	-5.317	4.330	-4.919
3	331.148	86.821	2.740	-6.068	4.643	-5.493
4	432.350	165.003*	4.340*	-7.921	6.057*	-7.168

Table A.4: Johansen tests for co-integration

maximum rank	trace statistic	5 % critical value	max statistic	5 % critical value
None*	55.939	47.856	29.755	27.584
At most 1	26.185	29.798	15.256	21.132
At most 2	10.923	15.495	10.746	14.265
At most 3	0.183	3.841	0.183	3.841

Notes:* denotes that it contains cointegrating equation

Table A.5: Long run FECM Result

Variable	Long run coefficient	t- statistics
LOGGDP(-1)	1.000	
F1(-1)	-0.268	-7.094
F2(-1)	0.012	0.405
F3(-1)	-0.110	-4.190

Table A.6: Short run FECM Result

Error Correction:	D(LOGGDP)	D(F1)	D(F2)	D(F3)
CointEq1	-0.094	2.043	-6.223	0.806
	[-1.204]	[4.155]	[-3.914]	[1.062]
D(LOG GDP(-1))	-0.810	-3.617	10.962	-6.152
	[-3.839]	[-2.734]	[2.562]	[-3.014]
D(F1(-1))	0.434	-1.134	3.000	0.364
	[1.574]	[-0.656]	[0.537]	[0.136]
D(F2(-1))	0.173	-0.322	0.817	0.240
	[1.918]	[-0.570]	[0.447]	[0.274]
D(F3(-1))	0.087	0.426	-1.311	0.481
	[2.928]	[2.292]	[-2.180]	[1.675]
C	0.241	3.309	-10.556	3.856
	[2.185]	[4.780]	[-4.716]	[3.611]
TEMPERATURE	-0.003	-0.036	0.116	-0.046
	[-2.256]	[-4.206]	[4.204]	[-3.491]
CASH RESERVE RATIO	-0.004	0.030	-0.094	-0.005
	[-1.624]	[1.785]	[-1.721]	[-0.177]
CRUDE OIL PRICE	-3.67	-0.003	0.011	-0.001
	[-0.186]	[-2.544]	[2.508]	[-0.374]
RATIO OF COMPLETED PROJECT TO GDP	0.534	-1.637	5.191	3.286
	[1.997]	[-0.977]	[0.958]	[1.271]
R-squared	0.886	0.791	0.780	0.736
Log likelihood	199.326	30.471	-77.505	-9.421
Akaike AIC	-3.855	-0.184	2.163	0.683
Schwarz SC	-3.252	0.419	2.766	1.286

Notes: [] contains t-statistics values

Table A.7: FECM Forecasting Evaluation Result(1999q1 - 2021q3)

Combination tests (Null hypothesis: Forecast i includes all information contained in others)						
Forecast	F-stat	F-prob				
LOGGDP-F	NA	NA				
LOGGDP-FF	9.562	0.003				
Diebold-Mariano test (HLN adjusted)(Null hypothesis: Both forecasts have the same accuracy)						
Accuracy	Statistic	prob	prob	prob		
Abs Error	-11.446	0.000	0.000	1.000		
Sq Error	-5.267	0.000	0.000	1.000		
Evaluation statistics						
Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
LOGGDP-F	0.000	0.000	0.000	0.000	0.000	0.000
LOGGDP-FF	0.046	0.035	0.242	0.242	0.001	0.543
Simple mean	0.023	0.017	0.121	0.121	0.001	0.271