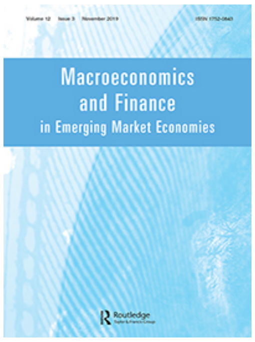

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Forecasting India's economic growth: a time-varying parameter regression approach

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ABSTRACT
Forecasting GDP growth is essential for effective and timely implementation of macroeconomic policies. This paper uses a principal component augmented Time Varying Parameter Regression (TVPR) approach to forecast real aggregate and sectoral growth rates for India. We estimate the model using a mix of fiscal, monetary, trade and production side-specific variables. To assess the importance of different growth drivers, three variants of the model are tried, namely, Demand-side, Supply-side and Combined models. We also find that TVPR model consistently outperforms constant parameter principal component augmented regression model and Dynamic Factor Model in terms of forecasting performance for all the three specifications.

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1. Introduction

Building an appropriate econometric model using multiple data series to produce timely and reasonably accurate forecasts has always been a challenge for econometricians. As Mongardini and Saadi-Sedik point out, 'The relevant statistics to judge the direction of economic activity are only available with a considerable lag, delaying the appropriate policy response' Mongardini and Saadi-Sedik (2003). Timely availability of statistical data is critical if forecasts of macroeconomic activities are to be useful for policymaking either by the government or by the corporate sector.

Additional challenges emerge in the process of obtaining accurate and reliable GDP growth forecasts in emerging economies like India such as incomplete and noisy data, short sample periods for which indicators may be available and the greater possibility of structural break in the economic time series as emerging economies are subject to rapid structural change and also changes in the policy regime. These complicate the choice of an appropriate model (Liu, Matheson, and Romeu 2012; Maier 2011).

This paper proposes and evaluates alternative forecasting models for real aggregate and sectoral annual growth rates of India, an emerging economy undergoing such rapid structural change along with major policy regime changes. We estimate India's aggregate and

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sectoral real GDP growth using Principal Component (PC) augmented Time-Varying Parameter Regression (PC-TVPR) approach following Eickmeier and Lemke (2015), Inoue, Jin and Rossi (2017) and Karakatsani and Bunn (2008). As opposed to pre-selection of a subset of variables explaining output growth from a pool of macroeconomic indicators, the PC-augmented regression approach allows us to extract information content from a large set of variables. The time-varying parameter variant of this approach additionally allows us to take account of the ongoing structural changes in the economy and policy and other shocks. The performance of the PC-TVPR is also compared with the performance of a constant parameter PC augmented model and also a dynamic factor model (DFM).

1.1. Antecedents and the PC-TVPR model

The use of a coincident indicator index, based on coincident indicators correlated with current economic activities, and a leading economic indicator index, based on leading indicators correlated with future economic activities, the approach pioneered by Mitchell and Burns (1938) and Burns and Mitchell (1946), was a major advance in summarizing and forecasting the state of macroeconomic activity. Subsequently, in their seminal work, Stock and Watson (1989) argued that the business cycle refers to co-movements in different economic activities and not just fluctuations in GNP; therefore, the reference cycle is best measured by looking at the co-movements of several aggregate time series driven by a common single unobserved or latent variable. The authors proposed a model to estimate this unobserved variable as representing the state of the economy. This unobserved variable refers to the 'current state of the economy and is a common element in the fluctuations of key aggregate time series variables' (Stock and Watson 1989). Such unobserved variables are estimated using a class of models known as DFM developed following Engle and Watson (1981), Geweke (1977) and Sarget and Sims (1977).

DFM is a time series extension of factor models which are used to deal with a large number of explanatory variables. DFM consists of a small number of unobserved dynamic factors that lead to the observed co-movements of macroeconomic series. When the common dynamic factors are driven by common economic shocks, identification of such shocks is essential for conducting policy analysis. These shocks, which may be embedded in a large number of variables, are efficiently handled by DFM. There is a large empirical literature that employs DFMs to capture the co-movements of macroeconomic time series with a small number of dynamic factors to predict business cycle movements or forecast economic growth for developed economies. More recently, applications of this technique have been extended to emerging economies, e.g. Corona, Gonzalez-Farias and Orraca (2017), Forni et al. (2001), Jiang, Guo and Zhang (2017) and Liu, Matheson and Romeu (2012).

Camba-Mendez et al. (2001) proposed to forecast GDP growth for European countries using a DFM as a tool to summarize the information content of a group of possible leading indicators, instead of preselecting the subset of variables as leading indicators from a pool of macroeconomic indicators. The method is similar to the leading index used by Stock and Watson (1989). As the information is selected automatically from a group of indicators, the model is described as an Automatic Leading Indicator (ALI) model (Camba-Mendez et al., 2001). The performance of the ALI model was assessed by comparing errors in its out-of-sample forecasts relative to the in-sample data set with that using alternative techniques. Camba-Mendez et al. (2001) found that forecasts based on the ALI method gave significantly better results compared to VAR models. Qin et al. (2008) compared the ALI method with macro econometric structural models (MESMs) in forecasting GDP growth and inflation and also found that the ALI method produces better forecasts than those based on MESMs. They suggested that the forecast of ALI could be improved by choosing the initial set of indicators based on theories. Banerjee, Marcellino and Masten (2005) also found that the ALI method provided significantly better forecasts as compared to traditional VAR models. However, they pointed out that the performance of ALI is quite sensitive to the choices of variables.

More recently, time-varying parameter models have been introduced in the literature to account for the unobserved structural changes occurring in an economy (Inoue, Jin, and Rossi 2017; Karakatsani and Bunn 2008). These have been found to outperform the conventional constant parameter models. The unobserved time-varying parameters are estimated in state-space form using the Kalman filtering technique (Karakatsani and Bunn 2008) or in rolling windows (Inoue, Jin, and Rossi 2017). The time-varying parameter models are also augmented with PC or factors as in Eickmeier and Lemke (2015) and Su and Wang (2017). This allows to summarize information from a large set of economic indicators instead of preselecting a set of indicators as in regression (single equation or vector autoregression) analysis.

This paper attempts to capture the turning points and forecast the growth of real GDP and real sectoral GDP growth for India using the PC-TVPR model as in Karakatsani and Bunn (2008), augmented with PCs as regressors. The PCs are estimated from a large set of macroeconomic indicators that include fiscal, monetary and trade indicators as well as production side-specific variables. The choice of possible leading indicators is based on an earlier study conducted by Chakravartti and Mundle (2017).

To better understand the role of different factors in driving aggregate and sectoral GDP growth in India, three variants of the model are tried. In the demand-side variant, the set of variables excludes production-specific indicators, while in the supply-side variant, information is extracted only from the latter set. The combined model combines both sets of variables. By classifying the set of leading indicators for growth into demand- and supply-side variables, our forecasting model provides useful insights on the relative strength of different factors in driving GDP growth in India.

Comparing the Root Mean Square Errors (RMSEs) of forecasts based on the demand side, supply side and combined variant shows that the demand-side model performs better than the other two specifications for industrial sector GDP, while the combined model gives the lowest RMSE for the agricultural sector GDP, service sector GDP and the aggregate real GDP.

We also compare the performance of the PC-TVPR model with those of a more conventional constant coefficient PC-augmented regression model and a DFM. We find that the time-varying parameter model outperforms the conventional models for all the three specifications mentioned above.

The rest of the paper is organized as follows. Section 2 outlines the estimation technique. Section 3 describes the data used in the analysis. The performance of the models in tracking growth rates over the sample period is discussed in Section 4. Section 5 compares performance of the PC-TVPR model with the two alternative models. Section 6 concludes the paper.

2. Model estimation

The model estimation consists of three steps:

- Step1: Extraction of factors by PC method.
- Step2: Regress GDP growth (total and sectoral) on the lagged factors using the time-varying parameter method.
- Step3: Deriving out-of-sample forecast of GDP growth using the estimated parameters and factors.

The model is as follows:

- Measurement equation:

$$y_t = \mathbf{F}'_t\beta_t + \epsilon_t \tag{1}$$

  where $\mathbf{F}_t$s is a $(k \times 1)$ vector of PCs estimated from the set of 'Demand-side', 'Supply-side' and 'Combined' macroeconomic indicators used for GDP growth forecast in our analysis.

- Transition equation

$$(\beta_{t+1} - \bar{\beta}) = \mathbf{G}(\beta_t - \bar{\beta}) + \mathbf{v}_{t+1} \tag{2}$$

  If the eigenvalues of the $(k \times k)$ matrix $\mathbf{G}$ are all inside the unit circle, then $\bar{\beta}$ has the interpretation as the average or steady-state value for the coefficient vector.
  Assuming that,

$$\left[\begin{array}{c|c} \mathbf{v}_{t+1} & \mathbf{F}_t, \mathbf{z}_{t-1} \\ \epsilon_t & \end{array}\right] \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \mathbf{Q} & \mathbf{0} \\ \mathbf{0}' & \sigma^2 \end{bmatrix}\right) \tag{3}$$

  where $z_{t-1} \equiv (y_{t-1}{}' y_{t-2}{}', \ldots, y_{1'}, F_{t-1}{}', F_{t-2}{}', \ldots., F_1')'$.

Here the regression coefficients β are not unknown constants but latent, stochastic variables that follow random walks, estimated by Hamilton (1994) and Kim and Nelson (1999). Equations (1)–(3) 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

$$y_t = \mathbf{F}'_t\bar{\beta} + \mathbf{F}'_t\mathbf{s}_t + \epsilon_t \tag{4}$$

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

$$\hat{\mathbf{s}}_{t|t} = \hat{\mathbf{s}}_{t|t-1} + \{\mathbf{P}_{t|t-1}\mathbf{H}(\mathbf{F_t})[\mathbf{H}(\mathbf{F_t})']\mathbf{P}_{t|t-1}\mathbf{H}(\mathbf{F_t}) + \mathbf{R}(\mathbf{F_t})]^{-1} \times [y_t - a(F_t) - \mathbf{H}(\mathbf{F_t})']\hat{\mathbf{s}}_{t|t-1}\} \quad (5)$$

$$\mathbf{P}_{t|t} = \mathbf{P}_{t|t-1} - \{\mathbf{P}_{t|t-1}\mathbf{H}(\mathbf{F_t})\times[\mathbf{H}(\mathbf{F}_t)']\mathbf{P}_{t|t-1}\mathbf{H}(\mathbf{F_t}) + \mathbf{R}(\mathbf{F_t})]^{-1}\mathbf{H}(\mathbf{F_t})']\mathbf{P}_{t|t-1}\} \quad (6)$$

$$s_{t+1}|\mathbf{F}_t, \mathbf{z}_{t-1} \sim N(\hat{\mathbf{s}}_{t+1|t}, \mathbf{P}_{t+1|t}) \quad (7)$$

$$\hat{\mathbf{s}}_{t+1|t} = \mathbf{G}\hat{\mathbf{s}}_{t|t} \quad (8)$$

$$\mathbf{P}_{t+1|t} = \mathbf{G}\mathbf{P}_{t|t}\mathbf{G}' + \mathbf{Q} \quad (9)$$

where $\mathbf{P}_{t|t} \equiv E[(s_t - \hat{s}_t)(s_t - \hat{s}_{t|t})']$ is the associated Mean Squared Error matrix and the least square forecast of the state vector on the basis of the data observed through period t is $\hat{\mathbf{s}}_{t+1|t} \equiv \hat{E}(\mathbf{s_{t+1}}|\mathbf{F}_t, \mathbf{z}_{t-1})$ which is the linear projection of $\hat{\mathbf{s}}_{t+1|t}$ on $\mathbf{F}_t$, $\mathbf{z}_{t-1}$ and a constant. A one step ahead forecast of y_t in Equation (1) can be calculated as:

$$E(y_t|\mathbf{F}_t, \mathbf{z}_t) = \mathbf{F}'_t\bar{\beta} + \mathbf{F}'_t\hat{\mathbf{s}}_{t|t=1} \quad (10)$$

3. Data

Time series data from 1980–1981 to 2016–2017 have been used to generate the forecast for the year 2017–2018. The set of demand-side and supply-side variables are listed in Table 1. As mentioned earlier, the starting set of indicators to forecast GDP growth in India is chosen following Chakravartti and Mundle (2017). The combined model combines the demand- and supply-side variables as the set of indicators for the forecasting exercise of the target indicator, namely GDP growth. The data description and sources are given in Table A.5 and A.6 in Appendix C

The supply-side indicators for the agriculture growth forecast include all the supply-side variables mentioned in Table 1. For the demand-side agriculture forecast, all the demand-side variables were included except the real non-food credit variable. Again for the demand-side industry forecast, all the demand-side variables are included except the

Table 1. List of variables for forecasting real GDP growth.

Demand side	Supply side
1. Stock of food grains	1. Imports of principal commodities – US dollar
2. Developmental expenditure of the central and state governments as % GDP at MP	2. Net capital stock
3. Non-developmental expenditure of the central and state governments as % GDP	3. Electricity generated
4. Real non-food credit	4. Employment in public and organized private sectors
5. Real effective exchange rate	5. Deviation of annual rainfall from normal level
6. Real interest rate	
7. Real money (M3)	
8. Foreign exchange reserves	
9. Fiscal deficit as % GDP at MP	
10. Rate of gross capital formation	
11. Ratio of export to import	

growth in stock of food grains. The rate of gross capital formation for agriculture here refers to capital formation related to agriculture sector. Similarly, for the forecast of growth in industry and services, the rate of capital formation refers to capital formation in the respective sectors. The rest of the variables in the demand-side and supply-side models for industry and services are the same as those used for the aggregate GDP growth forecast model.

The data series are at constant prices. The variables used in the model are tested for unit root using Augmented Dickey–Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. All the variables, except for the ratios and real interest rate, are transformed to their respective growth rates to make them stationary (see Tables A1–A3 in Appendix 1). The growth rates of the demand-side indicators, the real interest rate and Fiscal Deficit to GDP ratio are found to be stationary by all the tests.

Among the supply-side indicators, variables are converted into their growth rates, except for the rainfall series which is found to be stationary by all the three tests. The growth rates of real net capital stock (NCS), aggregate as well as sectoral are found to be non-stationary by all the three tests and hence we conduct Zivot–Andrews test for unit root against the alternative of stationarity with a structural break (see Table A4 in Appendix 1). For all the aggregate and sectoral growth rates of NCS, we cannot reject the null of unit root at 1% level of significance. Hence, we take first difference of growth rates of these series for our analysis.[1]

Using the transformed series, the PCs are estimated for the three different models. In the literature, components with eigenvalue greater than 1 are generally retained following Kaiser rule (Nardo et al. 2005). We follow this rule in our analysis also. However, given the limited time span of our data, we can only use at most four components in the TVPR analysis.[2]

4. Tracking growth rate in India

The reference period of the exercise starts from 1980–1981, the period when liberalization was initiated. The economy experienced a distinct increase in its growth rate from 1980–1981. The economy has also undergone significant structural change in the composition of GDP during this period, with a large decline in the share of agriculture and a large increase in services. The change in the share of industry has been modest (Figure 1 and Table 2).

- Note 1: Data from 1980–1981 to 2010–2011 are at 2004–2005 prices and from 2011–2012, the data are at 2011–2012 prices. The two series are chainlinked to convert the series from 1980–1981 to base year 2011–2012.[3]
- Note 2: (1) Agriculture = agriculture, forestry and fishing, (2) Industry = mining and quarrying + manufacturing + electricity, gas and water supply + construction and (3) Services = trade, hotels and restaurants + transport, storage and communication + financing, insurance, real estate and business services + community, social and personal services

GDP growth has been led primarily by services, especially financing; insurance; real estate and business services; and trade, hotels and restaurants. Accordingly, the share of services

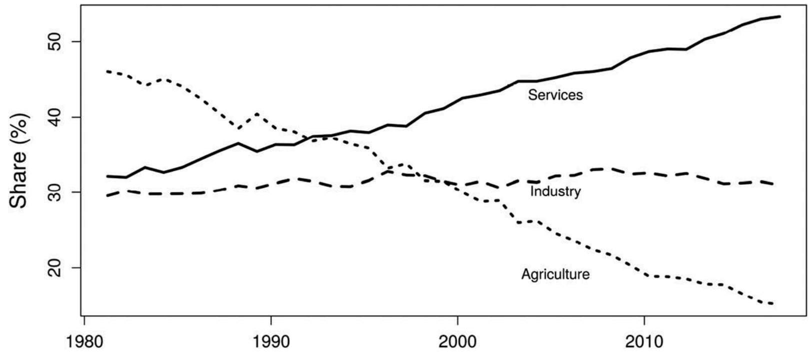

Figure 1. Share of agriculture, industry and services in GDP from 1980–1981 to 2016–2017.
Source: National Accounts Statistics, CSO.

Table 2. Share of agriculture, industry and services in GDP at 2011–2012 prices.

	Share in GDP (%) in 2011–2012 prices		
Sector	1980–1981	2011–2013	2016–2017
Agriculture	46.00	18.53	15.00
Industry	29.55	32.50	31.00
Services	32.11	49.00	53.38

Source: National Accounts Statistics, CSO and Authors' calculation.

increased sharply from 32% in 1980–1981 to 53% in 2016–2017. On the other hand, the share of agriculture declined from 46% in 1980–1981 to 15% in 2016–2017 and the share of industry moderately increased from 30% in 1980–1981 to 31% in 2012–2013.

4.1. Tracking growth in agriculture

Although the green revolution and technological advancement have substantially increased the production of major crops, the lack of adequate irrigation and inadequate input use have constrained growth in this sector. Growth is also volatile because the sector is still highly dependent on rainfall, which is a major determinant of growth in the sector (Dev 2012). Other important challenges faced by the sector include land scarcity relative to availability of labour; inadequate access to credit, consequent shortfall in input use and low productivity; soil erosion; inadequate storage facilities; lack of cold chains for some products, etc. (Dwivedy 2011).

The sector accounted for 15% of GDP in 2016–2017. During the last 16 years agricultural growth was positive in all the years except 2002–2003 and 2014–2015 (Figure 2). In 2002–2003, agriculture suffered from a severe drought and the negative growth in 2014–2015 is attributable to weak monsoons for two successive years.

The growth forecast for agriculture in 2017–2018 is based on the list of indicators given in Table 1. We derive factors from the indicators by the PC method. Table 3 shows the proportion of variance explained by the PCs estimated from each of demand side, supply side and the combined set of indicators. Although the first four components from

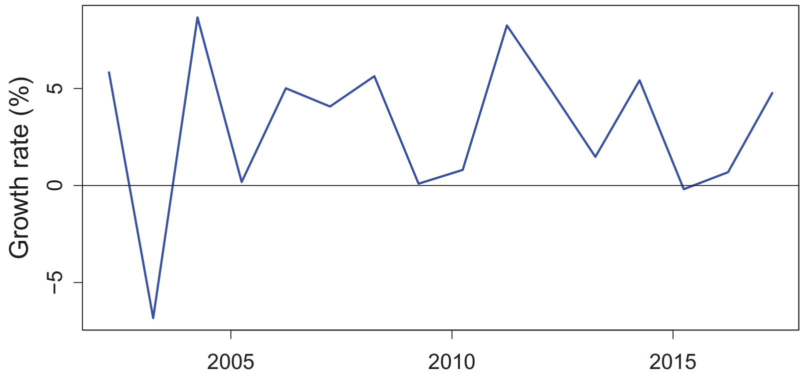

Figure 2. Growth rate of agriculture: 2001–2016.
Source: National Accounts Statistics, CSO.

Table 3. Proportion of agriculture growth variance explained by successive components.

	Components				
Variance proportion (%)	F1	F2	F3	F4	Cumulative variance share
Demand model	29.69	16.24	13.30		59.23
Supply model	33.86	26.94	17.59		78.39
Combined model	24.32	15.98	11.52	10.60	62.42

Source: Authors' calculation.

the demand-side indicators are found to have eigenvalue greater than 1, we retain only three components to be used for the dynamic coefficient regression model given the limited length of our data set.

The three components of the demand model explain 59.23% of the total variation in agricultural growth. In the supply-side model, the first three components explain 78.39% of total variation. For the combined model, we find six PCs with eigenvalue greater than 1. However, given the small span of the data, we use the first four components which explain more than 60% of the variation in the data.

Figure A1 in Appendix 2 depicts the fit of the three alternative models in tracking the agricultural GDP growth using our TVPR model.

4.2. Tracking growth in industry

Industry contributed 31% of total GDP in 2016–2017, with manufacturing constituting the largest component within the sector. The industry sector grew at positive rates in all the years from 2001 to 2016, with the highest growth of 11.48% being recorded in 2006 as shown in Figure 3.

The proportion of variance explained by the PC factors derived from the indicators listed in Table 1 is given in Table 4. We choose three factors for each of the Demand-side and Supply-side models, while four factors are considered for the Combined variant. The cumulative variance explained by the selected factors under the three model variants are

Figure 3. Growth rate of industry: 2001–2016.
Source: National Accounts Statistics, CSO.

Table 4. Proportion of industrial growth variance explained by successive components.

	Components				
Variance proportion (%)	F1	F2	F3	F4	Cumulative variance share
Demand model	31.55	17.82	15.46		64.83
Supply model	36.44	28.50	15.69		80.63
Combined model	25.75	17.26	11.18	10.65	64.84

Source: Authors' calculation.

64.83%, 80.63% and 64.84%, respectively. Figure A2 in Appendix 2 depicts the fit of the three alternative models in tracking the industrial GDP growth using the TVPR model.

4.3. *Tracking growth in services*

Following the initiation of liberalization in 1980s, services sector growth accelerated in the 1990s, significantly increasing its share in GDP. It is now the largest sector in the economy, accounting for 53% of total GDP in 2016–2017, with trade, hotels, restaurants and real estate constituting the largest components. Growth of services sector for the last 16 years is presented in Figure 4.

Table 5 presents the proportion of variance in growth of services sector explained by the PCs. We choose three factors for each of the Demand-side and Supply-side models, while four factors are considered for the Combined variant. The cumulative variance explained by the selected factors under the three model variants are 59.23%, 79.90% and 65.54%, respectively. Figure A3 in Appendix 2 depicts the fit of the three alternative models in tracking the industrial GDP growth using the TVPR model.

4.4. *Tracking aggregate GDP growth*

Finally, we come to the real GDP growth forecast. For each of the three models, demand side, supply side and combined, second to fifth column in Table 6, present the

Figure 4. Growth rate of services: 2001–2016.
Source: National Accounts Statistics, CSO.

Table 5. Proportion of services growth variance explained by successive components.

	Components				
Variance proportion (%)	F1	F2	F3	F4	Cumulative variance share
Demand model	29.69	16.24	13.30		59.23
Supply model	36.16	28.16	15.58		79.90
Combined model	25.02	18.31	11.50	10.61	65.54

Source: Authors' calculation.

Table 6. Proportion of real GDP growth variance explained by successive components.

	Components				
Variance proportion (%)	F1	F2	F3	F4	Cumulative variance share
Demand model	31.85	19.76	15.24		66.85
Supply model	33.65	26.78	17.11		77.54
Combined model	24.77	16.16	10.94	10.54	62.42

Source: Authors' calculation.

proportion of variation explained by individual components. The last column presents the cumulative variance explained by all the factors taken together. Figure A4 in Appendix 2 shows how the demand, supply and the combined model track the real GDP growth over the last three and half decades.

5. Evaluation of model performance

Comparison among the demand, supply and combined models based on the RMSE shows that the demand-side model performs better than the other two specifications for Industry, while the combined model gives lowest RMSE for aggregate GDP, Agriculture and Services.

In order to evaluate the performance of the PC-TVPR model, we compare RMSE values for each of demand, supply and combined models for each sector estimated using the PC-TVPR framework, with those estimated using Constant Coefficient Regression framework and a DFM. The alternative models are outlined in brief as follows:

Constant Coefficient Regression Model:

$$y_{it} = c + \sum_{j=1}^{n} a_j PC_{ijt} + u_{it}, \tag{11}$$

where y_i denotes output in the ith sector, and i belongs to GDP, GVA Agriculture, GVA Industry and GVA Services. Here j denotes the number of PCs used in the estimation for the respective sector. For all the sectors, four PCs with eigenvalue greater than 1 are used for the demand-side model, and three PCs with eigenvalue greater than 1 are estimated for the supply-side model. Under the combined model framework, six PCs with eigenvalues greater than 1 are used for GDP, Agriculture and Services sector, while five PCs having eigenvalue greater than 1 are used for the Industry.

Table 7 compares forecast performance of constant versus time-varying coefficients models on the basis of RMSE evaluated under the two modelling frameworks. The RMSEs for all the demand, supply and combined models for all the sectors evaluated under the TVP model relative to those evaluated under the constant coefficient model are less than one, indicating that the TVP model performs better than the constant coefficient models in tracking the aggregate and sectoral growth rates.

Dynamic Factor Model

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

$$y_t = As_t + By_{t-1} + e_t \tag{12}$$

$$s_t = C + \phi s_{t-1} + u_t \tag{13}$$

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 and C are parameters to be estimated and e_t and u_t are modelled as Gaussian error terms $e_t \sim iid \quad N(0, R)$, $u_t \sim iid \quad N(0, Q)$, 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 (13) is the transition equation which describes the

Table 7. Absolute and relative RMSE with respective to constant coefficient model.

	Demand model		Supply model		Combined model	
	Absolute	Relative	Absolute	Relative	Absolute	Relative
Constant parameter model						
–Agriculture	4.67		3.47		3.18	
–Industry	2.68		1.99		2.13	
–Services	1.81		1.50		1.26	
–GDP	4.61		1.85		1.70	
Time-varying parameter model						
–Agriculture	1.97	0.42	1.62	0.47	1.26	0.40
–Industry	0.83	0.31	0.98	0.49	1.00	0.47
–Services	0.80	0.44	0.78	0.52	0.69	0.55
–GDP	0.89	0.19	0.98	0.53	0.78	0.46

dynamics of unobserved variables. All the variables in the model are required to be stationary. Model estimation consisted of two steps:

1. Step 1: Extraction of factors by PC method.
2. Step 2: Forecasting y_t from Equation (13) using the extracted factors.

The model estimation aims at estimating the parameters A, B and 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 and Q.

Table 8 compares forecast performance of DFM versus time-varying coefficients models on the basis of RMSE evaluated under the TVP model and the DFM model. Given the short span of the time series, there are not sufficient degrees of freedom to estimate the DFM model with all the demand-side indicators. Hence we estimate the demand-side model under the DFM framework using the indicators having a correlation with aggregate and sectoral GDP growths greater than 0.2. Also due to the annual time series used in our analysis, we can not estimate the combined model under the DFM framework.[4]

The RMSEs for both the demand- and supply-side models for all the sectors evaluated under the TVP model relative to those evaluated under the DFM model are less than one, indicating that the TVP model performs better than the DFM model in tracking the aggregate and sectoral growth rates.

5.1. Forecast performance for 2017–2018

Table 9 gives the forecast of growth rate of GDP and all the sectoral GVAs for 2017–2018 and compares them with the actual outcomes in 2017–2018. Among all the three models, the combined model giving the lowest RMSE predicts aggregate GDP growth for 2017–2018 to be 6.78, which is closest to the actual outcome of 6.68% growth.

Table 8. Absolute and relative RMSE with respective to dynamic factor model.

	Demand model		Supply model	
	Absolute	Relative	Absolute	Relative
Constant parameter model				
–Agriculture	0.84		0.88	
–Industry	0.84		0.90	
–Services	0.91		0.92	
–GDP	0.96		0.96	
Time-varying parameter model				
–Agriculture	0.48	0.57	0.39	0.44
–Industry	0.33	0.39	0.39	0.43
–Services	0.50	0.55	0.48	0.52
–GDP	0.32	0.33	0.49	0.51

Table 9. Out of sample forecast performance.

	Actual	Demand side	Supply side	Combined
GDP	6.68	5.23	7.44	**6.78**
Agriculture	3.37	4.40	**3.65**	5.14
Industry	5.31	**5.05**	4.47	4.02
Services	7.36	7.01	**7.54**	8.54

The numbers in bold indicate the forecasts for the aggregate and sectoral growth obtained under a model variant that is closest to the actual outcome.

The supply-side variant of the model predicts 3.65% growth in agriculture for 2017–2018. This is the closest to the actual outcome of 3.37% of growth during the same period, although it is noted earlier that the forecast error based on RMSE is minimized using the combined model for this sector. Since the RMSE is an average over the sample period, there is nothing unusual about the supply-side variant giving a better forecast for a particular year. However, it does suggest that it may be prudent to present forecasts as a range incorporating all three variants. The demand-side variant predicts an industrial sector GDP growth of 5.05% during 2017–2018 which is nearest to the actual outcome of 5.54% growth. Again the supply-side variant predicts 7.54% growth for the services sector during 2017–2018 which is closest to the actual outcome of 7.36% of growth in this sector during the same period

6. Conclusion

This paper attempts to capture the turning points and forecast the growth of real GDP and real sectoral GDP growth for India using the TVPR model augmented with PCs as regressors, estimated from a large set of macroeconomic indicators. We estimate the model using a mix of fiscal, monetary, trade and production side-specific variables.

To understand the role of structural shocks in driving aggregate and sectoral GDP growth in India, three variants of the model are tried. In demand-side model, the set of variables exclude production-specific indicators, while in the supply-side model, information is extracted only from the latter set. The combined model combines both sets of variables. By classifying the set of leading indicators for growth into demand- and supply-side variables, our forecasting model provides useful insights on the relative strength of structural shocks in driving GDP growth in India.

Comparison among the demand, supply and combined models based on the RMSE shows that the demand-side model performs better than the rest of the two specifications for the Industry, while the combined model gives lowest RMSE for the aggregate GDP, Agriculture and Services.

We compare the performance of the PC-TVPR model with those of DFM and more conventional models of constant coefficient PC-augmented regression model. We find that the time-varying parameter model outperforms the conventional models for all the three specifications mentioned above. Although we find that TVPR model outperforms a DFM in tracking aggregate and sectoral GDP growth in India, a DFM using rolling window of samples or with time-varying loadings would be worth exploring to track Indian GDP growth.

Notes

1. In the set of supply-side variables, the aggregate and sectoral Net Capital Stocks (NCS) are available till 2015–2016. We use forecasted values for change in growth rates for the period 2016–2017 using AR(1) models for the aggregate NCS and NCS in Agriculture and Services. For the Industrial sector, we use a naive model to obtain the forecast.
2. Although in our supply-side analysis for all the sectors two components are found to have eigenvalue greater than 1, we include three components as that improves the forecast performance.
3. The Committee on Real Sector Statistics, National Statistical Commission and Government of India have published the back series prior to 2011–2012 with base year 2011–2012 using

production shift approach. However, this series is available from 1993 to 1994. Hence we have not used this series in our analysis.

4. Since the DFM models are estimated using the indicators standardized as a deviation from its respective mean and standard deviation, we also calculate RMSEs from the TVP model after standardizing the actual and predicted series.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendices

Appendix 1.

Table A1. Results of ADF unit root test for variables used in the analysis.

	Test statistic	
Variable	Series in level	First difference of series
Real GDP	−1.2431	−3.5456
GVA Agriculture	−3.3258	−5.4698
GVA Industry	−2.5893	−3.8652
GVA Services	−1.2662	−2.4215
GCF	−1.8209	−3.8502
GCF Agriculture	−2.1873	−4.949
GCF Industry	−2.4702	−4.4552
GCF Services	−2.0567	−4.1458
Food grains stock	−4.3983	−5.4543
Real non-food credit	−1.8622	−2.1099
Real M3	−1.549	−2.4703
Real foreign ex. reserve	−1.7869	−2.1099
REER	−2.8681	−4.8116
Real interest rate	−2.0007	−5.7164
Dev exp./GDP	−1.599	−3.6857
Nondev exp./GDP	−1.6195	−3.8951
Fiscal deficit/GDP	−3.5245	−5.4463
Export/Import	−1.6455	−4.0493
Imports of Principal Commodities (Real Rs.)	−2.0549	−3.1009
NCS (Real)	0.676	−1.0987
NCS Agriculture (Real)	2.1569	−0.3703
NCS Industry (Real)	−3.2202	−2.4043
NCS Services (Real)	−1.5905	−1.4338
Electricity generated	−2.2855	−2.6457
Employment	−1.5737	−2.3155
Deviation of rainfall	−4.448	

We conduct ADF test of the variables in log levels with drift and trend except for real interest rate and the ratios. The critical values for the specification with drift and trend, at 1%, 5% and 10% significance levels, are respectively −4.15, −3.50 and −3.18. We conduct ADF tests of real interest rate, the ratios, and growth rates of other macroeconomic indicators with drift. The critical values for the specification with drift, at 1%, 5% and 10% significance levels, are respectively −3.58, −2.93 and −2.60.

Table A2. Results of PP unit root test for variables used in the analysis.

	Test statistic	
Variable	Series in level	First difference of series
Real GDP	−0.9591	−4.8882
GVA Agriculture	−5.199	−12.1246
GVA Industry	−1.9003	−4.3313
GVA Services	−1.4356	−4.0801
GCF	−1.9547	−7.6423
GCF Agriculture	−3.4116	−9.0319
GCF Industry	−2.6909	−6.0156
GCF Services	−2.5288	−7.5167
Food grains stock	−2.7599	−3.8907
Real non-food credit	−1.7252	−3.2527
Real M3	−1.6835	−3.3935
Real foreign ex. reserve	−2.7934	−5.3415
REER	−2.5553	−5.6599
Real interest rate	−3.2295	−10.3438
Dev exp./GDP	−1.4807	−4.668
Nondev exp./GDP	−2.2424	−6.4437
Fiscal deficit/GDP	−3.242	−6.1582
Export/Import	−2.1205	−7.4895
Imports of Principal Commodities (Real Rs.)	−2.288	−4.3921
NCS (Real)	1.1559	−2.0914
NCS Agriculture (Real)	3.3065	−0.9718
NCS Industry (Real)	−1.909	−2.3507
NCS Services (Real)	−0.9636	−1.6845
Electricity generated	−1.2037	−4.9864
Employment	−2.4605	−4.2599
Deviation of rainfall	−4.481	

We conduct PP test of the variables in log levels with drift and trend except for real interest rate and the ratios. The critical values for the specification with drift and trend, at 1%, 5% and 10% significance levels, are respectively −4.23, −3.54 and −3.20. We conduct PP tests of real interest rate, the ratios and the growth rates of other macroeconomic indicators with drift. The critical values for the specification with drift, at 1%, 5% and 10% significance levels, are respectively −3.63, −2.95 and −2.61.

Table A3. Results of KPSS unit root test for variables used in the analysis.

	Test statistic	
Variable	Series in level	First difference of series
Real GDP	0.2532	0.5459
GVA Agriculture	0.0688	0.0554
GVA Industry	0.206	0.1967
GVA Services	0.256	0.6142
GCF	0.1928	0.1212
GCF Agriculture	0.1722	0.1438
GCF Industry	0.068	0.1016
GCF Services	0.2277	0.2632
Food grains stock	0.0448	0.0458
Real non-food credit	0.1786	0.1438
Real M3	0.128	0.1458
Real foreign ex. reserve	0.1303	0.1916
REER	0.1205	0.1426
Real interest rate	0.3821	0.0917
Dev exp./GDP	0.4627	0.1383
Nondev exp./GDP	0.3307	0.2604
Fiscal deficit/GDP	0.1074	0.0902
Export/Import	0.2075	0.2102
Imports of Principal Commodities (Real Rs.)	0.1357	0.1655
NCS (Real)	0.2496	0.7813
NCS Agriculture (Real)	0.248	0.8084
NCS Industry (Real)	0.1351	0.0749
NCS Services (Real)	0.2565	0.8145
Electricity generated	0.2197	0.3093
Employment	0.1327	0.2127
Deviation of rainfall	0.456	

The presence of unit root in the log level of the series except for real interest rate and the ratios is tested with the null that series are stationary around a deterministic trend. The critical values at 1%, 5% and 10% significance levels are respectively 0.216, 0.146 and 0.119. The presence of unit root in the real interest rate, the ratios and the growth rate of other macroeconomic indicators is tested with the null that the series are stationary around a constant. Critical values at 1%, 5% and 10% significance levels are respectively 0.739, 0.463 and 0.347.

Table A4. Results of Zivot–Andrews unit root test against structural breaks.

Variable	Test statistic
NCS	−5.1364
NCS Agriculture	−5.0331
NCS Industry	−3.1509
NCS Service	−4.8526

The null of unit root in the growth rate of the series against the stationarity with structural break is tested. The critical values at 1%, 5% and 10% are respectively −5.34, −4.8 and −4.58.

Appendix 2

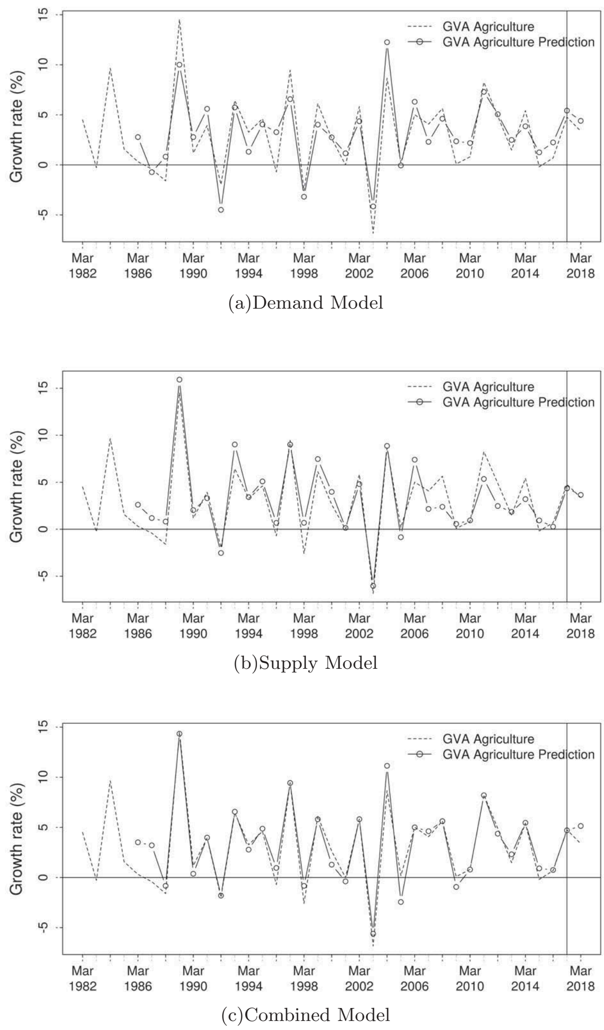
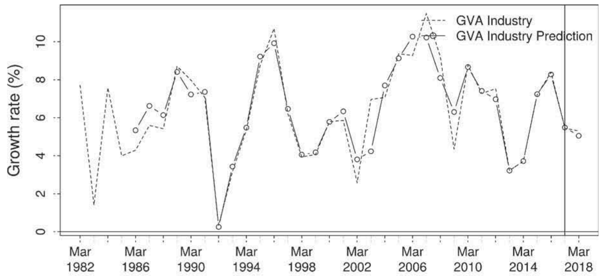
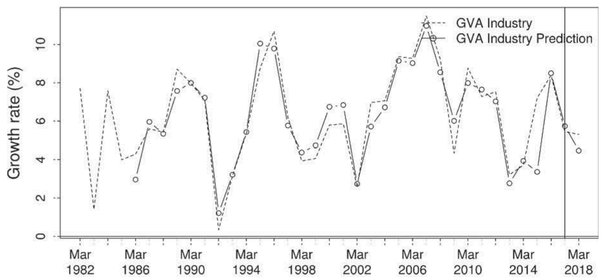


Figure A1. Agricultural growth tracking.

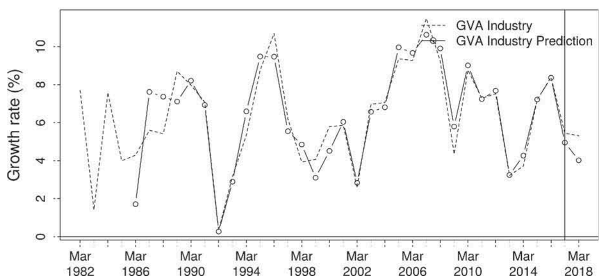
Source: Author's estimates.



(a)Demand Model

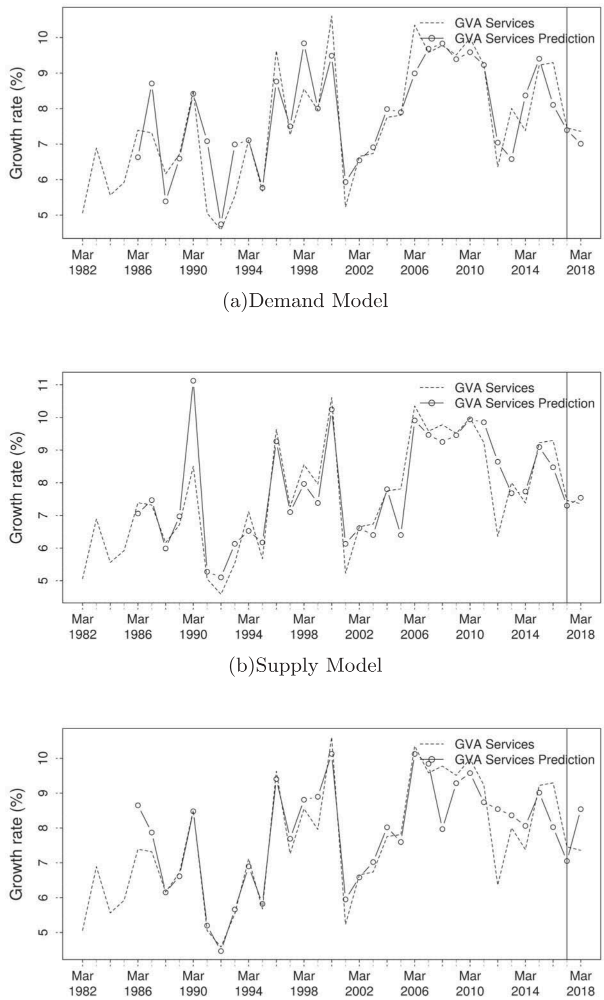


(b)Supply Model



(c)Combined Model

Figure A2. Industrial growth tracking.
Source: Author's estimates.

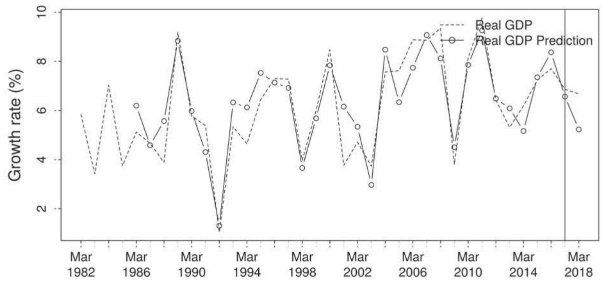


(a)Demand Model

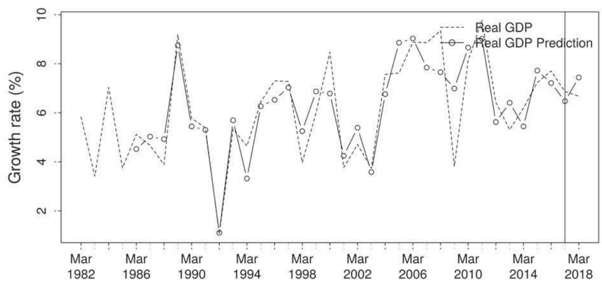
(b)Supply Model

(c)Combined Model

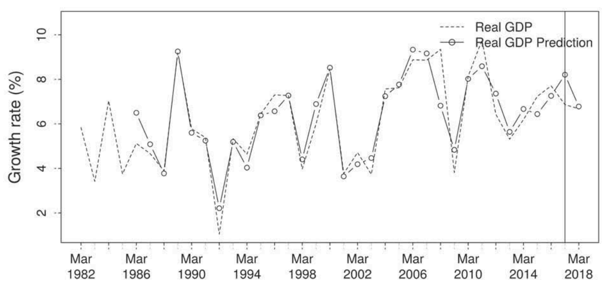
Figure A3. Services growth tracking.
Source: Author's estimates.



(a)Demand Model



(b)Supply Model



(c)Combined Model

Figure A4. Real GDP growth tracking.

Source: Author’s estimates.

Appendix 3

Table A5. Demand-side variables and data sources.

Indicators	Source	Unit
Growth rate of GDP at market price (2004–2005 prices)	Computed from CSO, Press Releases & Statements, summary of macroeconomic aggregates at current prices, 1950–1951 to 2013–2014 and summary of macroeconomic aggregates at constant (2004–2005) prices, 1950–1951 to 2013–2014.	INR crore
Growth rate of GDP at market price (2011–2012 prices)	Computed from CSO, Press Releases & Statements, annual and quarterly estimates of GDP at current and constant prices, 2011–2012 series and growth rates from 2012–2013 to 2015–2016-economic survey 2015–2016,vol-2.	INR crore
Growth rate of agricultural sector's GDP (2011–2012 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004–2005 prices and National Accounts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011–2012) prices (from 2011–2012 to 2013–2014) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and constant prices, 2011–2012 series (for 2014–2015 1st RE)	Per cent
Growth rate of industrial sector's GDP (2011–2012 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004–2005 prices and National Accounts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011–2012) prices (from 2011–2012 to 2013–2014) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and constant prices, 2011–2012 series (for 2014–2015 1st RE)	Per cent
Growth rate of service sector's GDP (2011–2012 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004–2005 prices and National Accounts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011–2012) prices (from 2011–2012 to 2013–2014) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and constant prices, 2011–2012 series (for 2014–2015 1st RE)	Per cent
Rate of gross capital formation	National Accounts Statistics 2014, Statement 1: Macroeconomic Aggregates (from 1982–1983 to 2011–2012 at 2004–2005 prices) and Economic Survey 2015–2016, Table 0.1: Key Indicators) from 2012–2013 to 2014–2015 at 2011–2012 prices.	Per cent
Rate of gross capital formation in agriculture	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 14: Capital Formation By Industry Of Use (at constant prices 2004–2005) and National Accounts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011–2012)	Per cent
Rate of gross capital formation in industry	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 14: Capital Formation By Industry Of Use (at constant prices 2004–2005) and National Accounts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011–2012)	Per cent
Rate of gross capital formation in services	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 14: Capital Formation By Industry Of Use (at constant prices 2004–2005) and National Accounts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011–2012)	Per cent
Ratio of export to import (calculated)	RBI, Handbook of Statistics on Indian Economy, Table 127: India's Foreign Trade – Rupees	Ratio
Developmental expenditure of the central and state governments	RBI, Handbook of Statistics on Indian Economy, Table 116: Developmental and Non-Developmental Expenditure of the Central and State Governments and for 2013–2014 to 2015–2016 HBS (Table 103: Major Heads of Developmental and Non-Developmental Expenditure of the Central Government) and State finances: A study of budgets, RBI (Table III.5: Expenditure Pattern of State Governments)	INR crore

(*Continued*)

Table A5. (Continued).

Indicators	Source	Unit
Non-Developmental Expenditure of the Central and State Governments	RBI, Handbook of Statistics on Indian Economy, Table 116: Developmental and Non-Developmental Expenditure of the Central and State Governments and for 2013–2014 to 2015–2016 HBS (Table 103: Major Heads of Developmental and Non-Developmental Expenditure of the Central Government) and State finances: A study of budgets, RBI (Table III.5: Expenditure Pattern of State Governments)	INR crore
Food credit	RBI, Annual Report, Sectoral Deployment of Gross Bank Credit	INR crore
Non-food credit	RBI, Handbook of Statistics on Indian Economy, Table 49: Sectoral Deployment of Non-Food Gross Bank Credit (Outstanding)	INR crore
Fiscal deficit	RBI, Handbook of Statistics on Indian Economy, Table 113: Combined Deficits of Central and State Governments	INR crore
Foreign exchange reserves	RBI, Handbook of Statistics on Indian Economy, Table 157: Foreign Exchange Reserves	US$ million
Broad money	RBI, Handbook of Statistics on Indian Economy, Table 46: Average Monetary Aggregates	INR crore
Real effective exchange rate (REER)	RBI, Handbook of Statistics on Indian Economy, Table 149: Indices of Real Effective Exchange Rate (REER) and Nominal Effective Exchange Rate (NEER) of the Indian Rupee (36 – Currency Bilateral Weights) (Financial Year – Annual Average)	Per cent
Stock of food grains	RBI, Annual Report, Macroeconomic and Financial Indicators and for 2015–2016-Economic Survey 2015–2016, vol-2 (Table 5.15: Public Distribution System – Procurement, Offtake and Stocks)	Per cent
Real interest rate (computed by deducting inflation from nominal interest rate) and weighted average lending rate)	RBI, Database On Indian Economy, Weighted average lending rate of SCBs for all loans and for major sectors – as on 31st March	Per cent

Table A6. Supply-side variables and data sources.

Indicators	Source	Unit
Net capital stock (at constant (2004–2005) prices) (as on 31st March)	MOSPI, CSO, Statement 15: Net capital stock by type of institutions, National Accounts Statistics Back Series 2011 and Statement 21: Net capital stock by type of institution, National Accounts Statistics 2014	INR crore
Net capital stock in agriculture (at constant (2004–2005) prices) (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004–2005 prices and Statement 22: Net capital stock by industry of use, National Accounts Statistics 2015	INR crore
Net capital stock in industry (at constant (2004–2005) prices) (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004–2005 prices and Statement 22: Net capital stock by industry of use, National Accounts Statistics 2015	INR crore
Net capital stock in services (at constant (2004–2005) prices) (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004–2005 prices and Statement 22: Net capital stock by industry of use, National Accounts Statistics 2016	INR crore
Electricity generated	Economic Survey 2015–2016, A43, Table 1.25: Progress of Electricity Supply (Utilities & Non-Utilities)	(Billion KWH)
Imports of principal commodities – US dollar	RBI, Handbook of Statistics, Table 130: Imports of Principal Commodities – US dollar	US$ million
Employment in public and organized private sectors	RBI, Handbook of Statistics, Table 15: Employment in Public and Organized Private Sectors	Million
Employment is computed by adding data on public and organized private sectors (due to data non-availability from 2012 to 2013, the data for 2011 is assumed for these years).	The public sector comprises all governmental agencies: Central, State, Quasi-Government (both Central and State) and local bodies. The private sector comprises all establishments (under the organized sector) employing 10 or more persons.	
Deviation of annual rainfall from normal level	CMIE Economic Outlook	Per cent