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 used. 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 consists of both sets of variables. We find that TVPR model consistently outperforms constant parameter factor-augmented regression model and Dynamic Factor Model in terms of forecasting performance for all the three specifications. Based on the TVPR model, we find that demand side variant minimises the error forecast for total GDP and the industrial sector GDP, while the supply side variant minimises the error forecast for services sector GDP. We also find that forecast error is minimised using both the supply side variant and the combined variant for agriculture sector GDP.

Keywords: Real GDP growth, Forecasting, Time Varying, Parameter Regression Model, Dynamic Factor Model, India

JEL Classification Codes: C32, C5, O4

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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 that, "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 made use of in policy making 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 et al., 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 sectoral real GDP growth using Factor-Augmented Time Varying Parameter Regression (FA-TVPR) approach as in Eickmeier and Lemke(2015); Inoue et al.(2017); Karakatsani and Bunn(2008). As opposed to pre-selection of a subset of variables explaining output growth from a pool of macroeconomic indicators, the factor-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 FA-TVPR is also compared with the performance of a constant parameter factor augmented model and also a dynamic-factor model.

1.1 Antecedents & the FA-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 Burns and Mitchell (Mitchell and Burns (1938), Burns & 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 Dynamic Factor Models (DFMs) which were developed following Engle and Watson (1981); Geweke (1977); Sargent 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 has been extended to emerging economies, e.g., Corona et al. (2017); Forni et al. (2001); Jiang et al. (2017); Liu et al. (2012).

Camba-Mendez et al. (2001) proposed to forecast GDP growth for European countries using a dynamic factor model as a tool to summarize the information content of a group of possible leading indicators, instead of pre-selecting 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 et al. (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 et al., 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 et al., 2017). The time-varying parameter models are also augmented with Principal Components (PC) or factors as in Eickmeier and Lemke (2015); and Su and Wang (2017). This allows to summarise information from a large set of economic indicators instead of pre-selecting a set of indicators as in regression (single equation or vector auto-regression) 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 Principal Component Augmented Time Varying Parameter Regression (PC-TVPR) model as in Karakatsani and Bunn (2008), augmented with Principal Components (PCs) as regressors. The PCs are estimated from a large set of macroeconomic indicators that includes 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).

In order to better understand the role of different factors in driving aggregate and sectoral GDP growth in India, we try three variants of the model. 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 consists of 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 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 aggregate GDP and industry, while the supply-side model gives the lowest RMSE for the service sector GDP. Both the supply-side and the combined variants perform equally well for agriculture.

We also compare the performance of the (PC-TVPR) model with those of a more conventional constant coefficient PC-augmented regression model and a dynamic factor model. 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

Estimation of the model consists of three steps:

Step 1: Extraction of principal components from the set of indicators.

Step 2: Regress GDP growth (total and sectoral) on the lagged principal components using the time-varying parameter method

Step 3: Deriving out-of-sample forecast of GDP growth using the estimated parameters and principal components.

The model is as follows:

- Measurement equation:

$$yt = F_t' \beta t + \in_t \qquad (1)$$

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

assuming that,

$$\begin{pmatrix} V_{t+1} \\ \in_t \end{pmatrix} \Big| F_{t,Z_{t-1}} \sim N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} Q & 0 \\ 0 & \sigma^2 \end{pmatrix}\right] \tag{3}$$

where $z_{t-1} \equiv (y'_{t-1}, y'_{t-2}, \ldots\ldots, y'_1, F'_{t-1}, F'_{t-2}, \ldots\ldots\ldots, F'_1)$

Here, the regression coefficients β are not unknown constants but latent, stochastic variables that follow random walks, estimated by Kalman Filter (Hamilton, 1994; Kim and Nelson, 1999). Equations 1, 2, and 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

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

which is an observation equation with $\mathbf{a}(\mathbf{F_t}) = F'_t\bar{\beta}$, $\mathbf{H}(\mathbf{F_t}) = \mathbf{F_t}$, and $\mathbf{R}(\mathbf{F_t}) = \sigma^2$. These values then used in the following Kalman Filter iterations:[5]

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

$$P_{t|t} = P_{t|t-1} - \{P_{t|t-1}\,H(F_t)\} \times [H(F_t)']P_{t|t-1}\,H(F_t) + R(F_t)]^{-1}H(F_t)'P_{t|t-1}\} \tag{6}$$

$$s_{t+1}|F_t, z_{t-1} \sim N(\hat{s}_{t+1|t}, P_{t+1|t}) \tag{7}$$

$$\hat{s}_{t+1|t} = G\hat{s}_{t|t} \tag{8}$$

$$P_{t+1|t} = GP_{t|t}G' + Q \tag{9}$$

where $\mathbf{P}_{t/t} \equiv E[(s_t - \hat{s}_t)(s_t - \hat{s}_{t/t})']$ is the associated Mean Squared Error (MSE) matrix and the least square forecast of the state vector on the basis of the data observed

5) see Hamilton, (1994) for details.

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 for y_t in equation 1 can be calculated as:

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

3. DATA

Time-series data from 1980-81 to 2016-17 has been used to generate the forecast for the year 2017-18. The set of demand side and supply side variables are listed in Table 3.1. As mentioned earlier, the starting set of indicators to forecast GDP growth in India are 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 supply side indicators for the agriculture growth forecast includes all the supply side variables mentioned in Table 3.1 above. 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 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 A.1, A.2, and A.3 in Appendix A). The growth rate 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 are 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 A.4 in Appendix A). For all the aggregate and sectoral growth rates of Net Capital Stock (NCS), we cannot reject the null of unit root at 1% level of significance. Hence, we take the first difference of growth rates of these series for our analysis.[6]

Using the transformed series, the principal components are estimated for the three different models. In the literature, components with eigen value 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 4 components in the time varying parameter regression analysis.

Table 3.1: List of Variables for forecasting Real GDP Growth

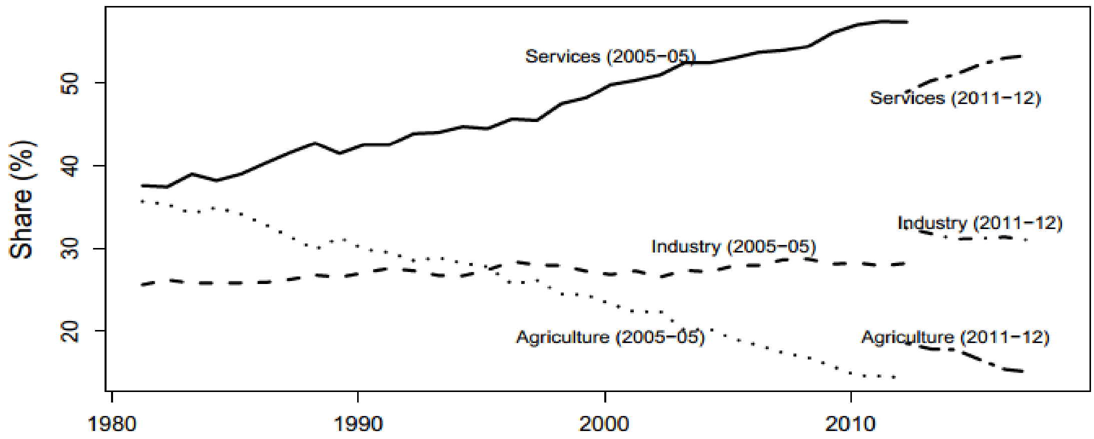
Demand Side	Supply Side
1. Stock of food grains	1. Imports of Principal Commodities – US Dollar
2. Developmental Expenditure of the Central and State Governments as % GDP at MP	2. Net capital stock
3. Non-Developmental Expenditure of the Central and State Governments as % GDP	3. Electricity Generated
4. Real Non-food credit	4. Employment in Public and Organised Private Sectors
5. Real Effective Exchange Rate	5. Rainfall in India during July
6. Real Interest Rate	6. Rainfall in India during De
7. Real Money (M3)	7. Rainfall in India during January, February, July, August, September and December
8. Foreign Exchange Reserves	
9. Fiscal Deficit as % GDP at MP	
10. Rate of gross capital formation	
11. Ratio of Export to Import	

6) In the set of supply side variables, the aggregate and sectoral Net Capital Stocks are available till 2015-16. We use forecasted values for change in growth rates for the period 2016-17 using AR (1) models for the aggregate NCS and Net Capital Stocks in Agriculture and Services. For the Industrial sector, we use a naive model to obtain the forecast. The rainfall data are available till 2014-15. We use the rainfall data for the year 2014-15 in 2015-16 and 2016-17 as well.

4. Tracking growth rate in India

The reference period of the exercise starts from 1980s, the period when liberalization was initiated. The economy experienced a distinct increase in its growth rate from 1980-81. 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 4.1: Share of Agriculture, Industry and Services in GDP from 1981 to 2014 (at 2004-05 prices and 2011-15 prices)



Source: National Accounts Statistics, CSO

- **Note 1:** Data from 1981-82 to 2010-11 are at 2004-05 prices and from 2011-12, the data are at 2011-12 prices.
- **Note 2:** (1) Agriculture = agriculture, forestry & fishing, (2) Industry = mining & quarrying + manufacturing + electricity, gas & water supply + construction (3) Services = trade, hotels & restaurants + transport, storage & communication +financing, insurance, real estate & business services+ community, social & 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 increased sharply from 38 per cent in 1981- 82 to 66 per cent in 2012-13. On the other hand, the share of agriculture declined from 35 per cent in 1981-82 to 16 per cent in 2012-13 and the share of industry increased from 26 per cent in 1981-82 to 30 per cent in 2012-13.

Figure 4.1 and Table 4.1 shows the share of agriculture, industry and services in overall GDP from 1981-82 to 2012-13 in 2004-05 prices and from 2011-12 to 2014-15 in 2011-12 prices. Comparing the sector shares in the overlapping years 2011-12 and 2012-13 in the two series we observe that shares of both agriculture and industry are higher and that of services lower in the new 2011-12 prices based series compared with the earlier 2004-05 prices based series. However, both the old and new series shows a declining trend in the shares of agriculture and a rising trend in the share of services. The share of industry is relatively stable.

Table 4.1: Share of Agriculture, Industry and Services in GDP at 2004-05 and 2011-12 prices

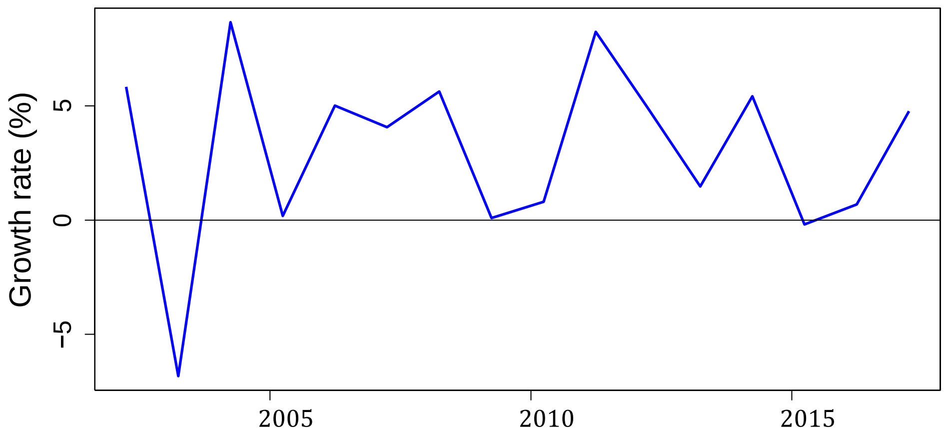
Sector	Share in GDP (%) in 2004-05 prices		Share in GDP (%) in 2011-12 prices	
	2011-12	2012-13	2011-12	2012-13
Agriculture	15.3	15.5	18.4	17.7
Industry	30.1	30.4	33.1	32.3
Services	61.3	65.5	48.5	50.0

Source: National Accounts Statistics, CSO & Authors' calculation

4.1 Tracking Growth in Agriculture

Although the green revolution and technological advancement has 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).

Figure 4.2: Growth Rate of Agriculture (2001 to 2016)



Source: National Accounts Statistics, CSO

The sector accounted for 16 per cent of GDP in 2014-15. During the last sixteen years agricultural growth was positive in all the years except 2002-03, and 2014-15 (Figure 4.2). In 2002-03, agriculture suffered from a severe drought and the negative growth in 2014-15 is attributable to weak monsoons for two successive years.

The growth forecast for agriculture in 2016-17 is based on the list of indicators given in Table 3.1. We derive factors from the indicators by the principal component method. Table 4.2 shows the proportion of variance explained by the principal components estimated from each of demand-side, supply-side, and the combined set of indicators. Although the first four components from the demand side indicators are found to have eigenvalue greater than 1, we retain only 3 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 53.39% of total variation. For the combined model, we find six principal components 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 B.1 in Appendix B depicts the fit of the three alternative models in tracking the agricultural GDP growth using our time-varying parameter regression model.

Table 4.2: Proportion of Agriculture Growth Variance Explained by Successive Components.

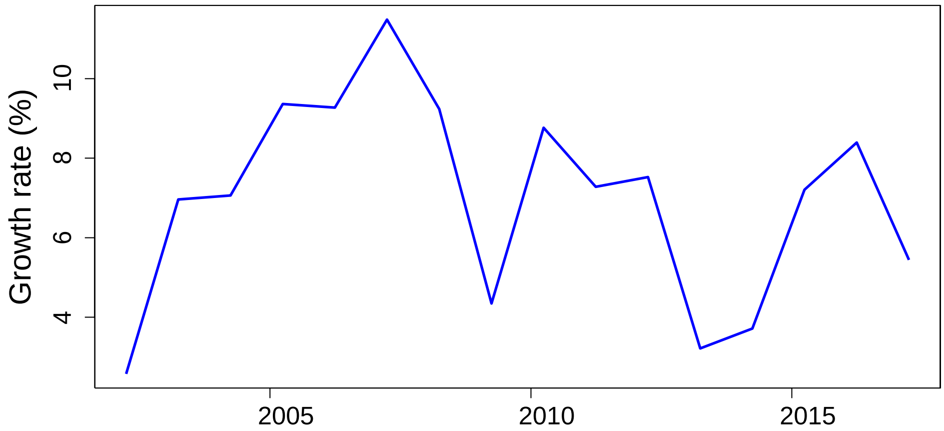
Variance Proportion %	Component 1 F1	Component 2 F2	Component 3 F3	Component 4 F4	Cumulative Variance Share
Demand Model	29.69	16.24	13.30		59.23
Supply Model	34.75	18.64	14.34		67.73
Combined Model	23.42	15.02	11.97	10.79	61.20

Source: Authors' calculation

4.2 Tracking Growth in Industry

Industry contributed 31 per cent of total GDP in 2016-17, 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 per cent being recorded in 2006 as shown in Figure 4.3.

Figure 4.3: Growth Rate of Industry (2001 to 2016)



Source: National Accounts Statistics, CSO

The proportion of variance explained by the principal component factors derived from the indicators listed above in Table 3.1 are given in Table 4.3. The cumulative variance explained by the selected factors, for all demand, supply and combined models are 64.83%, 71.10% and 52.52% respectively. Figure B.2 in Appendix B depicts the fit of the three alternative models in tracking the industrial GDP growth using the time-varying parameter regression model.

Table 4.3: Proportion of Industrial Growth Variance Explained by Successive Components

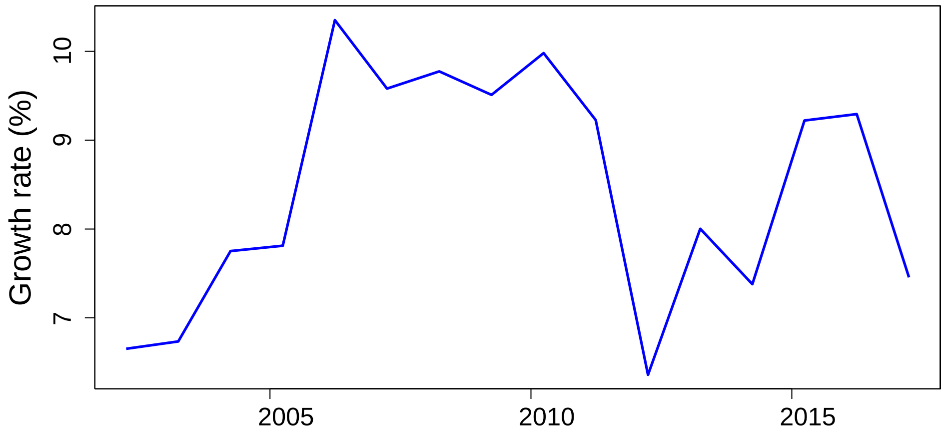
Variance Proportion (%)	Component 1 F1	Component 2 F2	Component 3 F3	Cumulative Variance Share
Demand Model	31.55	17.82	15.46	64.83
Supply Model	35.66	21.22	14.22	71.10
Combined Model	23.74	17.17	11.61	52.52

Source: Authors' calculation

4.3 Tracking Growth in Services

Following the initiation of liberalization in 1980s, services sector growth accelerated in the 1990s, significantly increasing its share of GDP. It is now the largest sector in the economy, accounting for 53 per cent of total GDP in 2014-15, with trade, hotels, restaurants and real estate, constituting the largest components. Growth of services sector for the last fifteen years is presented in Figure 4.4.

Figure 4.4: Growth Rate of Services (2001 to 2016)



Source: National Accounts Statistics, CSO

Table 4.4 presents the proportion of variance in growth of services sector explained by the principal component factors. The cumulative variance explained by the selected factors, three for all demand supply and combined models are 59.23%, 71.19% and 51.98% respectively. Figure B.3 in Appendix B depicts the fit of the three alternative models in tracking the industrial GDP growth using the time-varying parameter regression model.

Table 4.4: Proportion of Services Growth Variance Explained by Successive Components

Variance Proportion (%)	Component 1 F1	Component 2 F2	Component 3 F3	Cumulative Variance Share
Demand Model	29.69	16.24	13.30	59.23
Supply Model	34.55	21.27	15.49	71.19
Combined Model	23.61	16.28	12.09	51.98

Source: Authors' calculation

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 fourth column in Table 4.5 present the proportion of variation explained by individual components. The last column presents the cumulative variance explained by all the factors taken together. Figure B.4 in Appendix B shows how the demand, supply and the combined model track the real GDP growth over the last three and half decade.

Table 4.5: Proportion of Real GDP Growth Variance Explained by Successive Components

Variance Proportion (%)	Component 1 F1	Component 2 F2	Component 3 F3	Component 4 F4	Cumulative Variance Share
Demand Model	31.85	19.76	15.24		31.85
Supply Model	34.44	19.03	14.68		68.26
Combined Model	23.34	14.73	12.26	10.25	60.58

Source: Authors' calculation

5. Evaluation of model performance

Comparison among the Demand, Supply and Combined models based on the Root Mean Square Error shows that the Demand-side model performs better than the other two specifications for aggregate GDP and Industry, while the Supply-side model gives lowest RMSE for Services. Both Supply-side and the Combined model performs equally well for Agriculture.

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 Dynamic Factor Model. The alternative models are outlined in brief as follows:

Constant Coefficient Regression Model:

$$y_{it} = \mathrm{c} + \sum_{j=1}^{n} a_j \mathrm{P}C_{ijt} + u_{it} \tag{11}$$

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 principal components (PC) used in the estimation for the respective sector. For all the sectors, four PCs with eigen value greater than 1 are used for the demand side model, and three PCs with eigen value 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 5.1 compares forecast performance of constant versus time-varying coefficients models on the basis of Root Mean Square Error (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 Dynamic Factor Model (DFM) assumes that a common unobservable state variable s_t drives N number of macroeconomic indicators y_t. The framework of Dynamic Factor Model (DFM) is outlined as follows:

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

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

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

The DFM specification is a state-space model where the first equation, the measurement equation, describes the relation between the observed variable y_t and the unobserved state variable s_t. Equation (13) is the transition equation which describes the dynamics of unobserved variables. All the variables in the model are required to be stationary. Model estimation consisted of two steps:

Step 1: Extraction of factors by principal component method.

Step 2: Forecasting y_t from equation (13) using the extracted factors.

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

Table 5.1: 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	1.92	0.55	1.92	0.71
Industry	0.83	0.31	0.98	0.49	1.14	0.53
Services	0.80	0.44	0.37	0.25	0.52	0.41
GDP	0.89	0.19	1.11	0.60	1.18	0.69

Source: Authors' Estimates

Table 5.2 compares forecast performance of constant versus time-varying coefficients models on the basis of Root Mean Square Error (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 cannot estimate them Combined model under the DFM framework.[7]

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.

7) Since the DFM models are estimated using the indicators standardised as a deviation from its respective mean and standard deviation, we also calculate RMSEs from the TVPR model after standardising the actual and predicted series.

Table 5.2: 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	0.46	0.52
Industry	0.33	0.39	0.39	0.43
Services	0.50	0.55	0.22	0.24
GDP	0.32	0.33	0.54	0.56

5.1 Out of sample forecast performance for 2017-18

Table 5.3 gives the forecast of growth rate of GDP and all the sectoral GVAs for 2017-18 and compares them with the actual outcomes in 2017-18. Among all the three models, the combined model predicts aggregate GDP growth for 2017- 18 to be 6.65 which is closest to the actual outcome of 6.68% growth though it was noted earlier that the forecast error based on RMSE is minimised using demand-side variant.

Table 5.3: Out of sample forecast performance

	Actual	Demand side	Supply side	Combined
GDP	6.68	5.23	5.61	6.56
Agriculture	3.37	4.40	3.53	1.75
Industry	5.54	5.05	2.44	4.66
Services	7.92	7.01	8.00	8.59

Since the RMSE is an average over the sample period, there is nothing unusual about the 'combined' variant giving a better forecast for a particular year. However, it suggests that it may be prudent to present forecasts as a range incorporating all three variants.

The supply-side variant of the model predicts 3.53% growth in agriculture for 2017-18. This is the closest to the actual outcome of 3.37% of growth during the same period. The demand-side variant predicts an industrial sector GDP growth of 5.05% during 2017-18 which is nearest to the actual outcome of 5.54% growth. The supply-side variant predicts 8% growth for the services sector during 2017-18 which is closest to the actual outcome of 7.92% 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 a Time Varying Parameter Regression model augmented with Principal Components 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 Root Mean Square Error shows that the Demand-side model performs better than the rest of the two specifications for aggregate GDP and Industry, while the Supply-side model gives lowest RMSE for the Services. Both Supply-side and the Combined model performs equally well for Agriculture.

We compare the performance of the PC-Augmented Time Varying Parameter Regression (TVPR) model with those of Dynamic Factor model 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 TVP Regression model outperforms a Dynamic Factor Model in tracking aggregate and sectoral GDP growth in India, a Dynamic Factor model using rolling window of samples or with time-varying loadings would be worth exploring to track Indian GDP growth.

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Appendix A

Table A.1: Results of ADF Unit Root Test for variables used in the analysis

Variable	Test statistic	
	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 nonfood credit	-1.8622	-2.1099
Real M3	-1.549	-2.4703
Real foreign exchange reserve	-1.7869	-2.1099
REER	-2.8681	-4.8116
Real interest rate	-2.0007	-5.7164
Development expenditure/GDP	-1.599	-3.6857
Non-development expenditure/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
Rainfall in July	-4.1435	
Rainfall in December	-3.4000	
Rainfall in selected months	-3.183	

Note: 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 level, are respectively -4.15 -3.50 -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 level, are respectively -3.58, -2.93 and -2.60.

Table A.2: Results of Phillips-Perron Unit Root Test for variables used in the analysis

Variable	Test statistic	
	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 nonfood credit	-1.7252	-3.2527
Real M3	-1.6835	-3.3935
Real foreign exchange reserve	-2.7934	-5.3415
REER	-2.5553	-5.6599
Real interest rate	-3.2295	-10.3438
Development expenditure/GDP	-1.4807	-4.668
Non-development expenditure/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
Rainfall in July	-6.7314	
Rainfall in December	-4.7351	
Rainfall in selected months	-5.6245	

Note: 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 level, are respectively -4.23, -3.54, -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 level, are respectively -3.63, -2.95, -2.61.

Table A.3: Results of KPSS Unit Root Test for variables used in the analysis

Variable	Test statistic	
	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 nonfood credit	0.1786	0.1438
Real M3	0.128	0.1458
Real foreign exchange reserve	0.1303	0.1916
REER	0.1205	0.1426
Real interest rate	0.3821	0.0917
Development expenditure/GDP	0.4627	0.1383
Non-development expenditure/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
Rainfall in July	0.1662	
Rainfall in December	0.5145	
Rainfall in selected months	0.1644	

Note: The presence of unit root in the log level of the series except for real interest rate and the ratios are tested with the null that series are stationary around a deterministic trend. The Critical values at 1%, 5% and 10% significance level 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 are tested with the null that the series are stationary around a constant. Critical values at 1%, 5% and 10% significance level are respectively 0.739, 0.463, and 0.347.

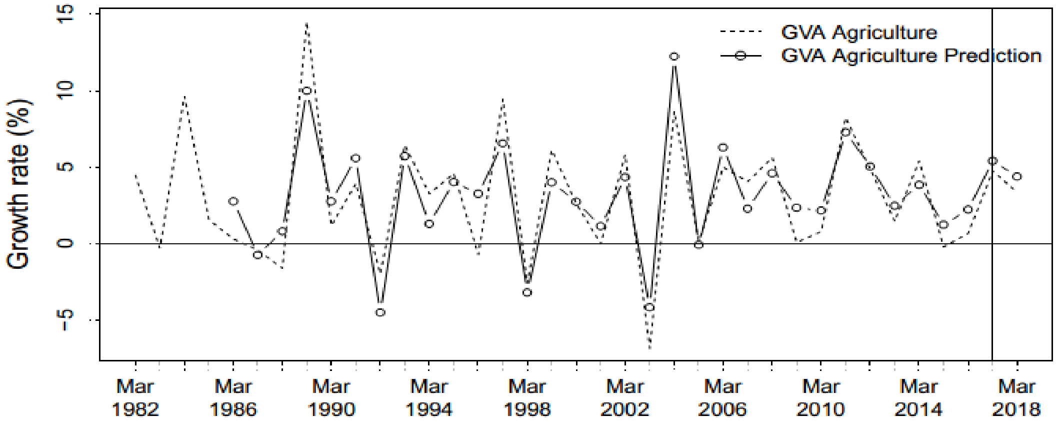
Table A.4: Results of Zivot Andrews Unit Root Test against structural breaks:

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

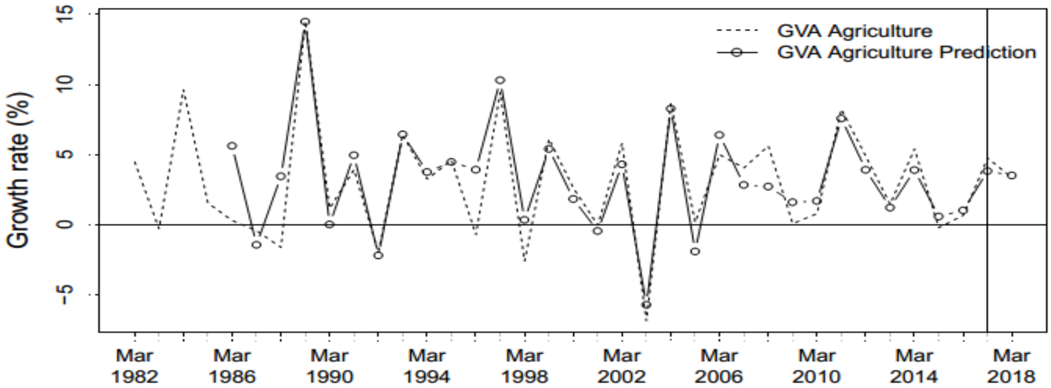
The null of unit root in the growth rate of the series against the stationarity with structural break is tested. The critical values at 1%, 5% and 10% are respectively -5.34, -4.8, and -4.58.

Appendix B

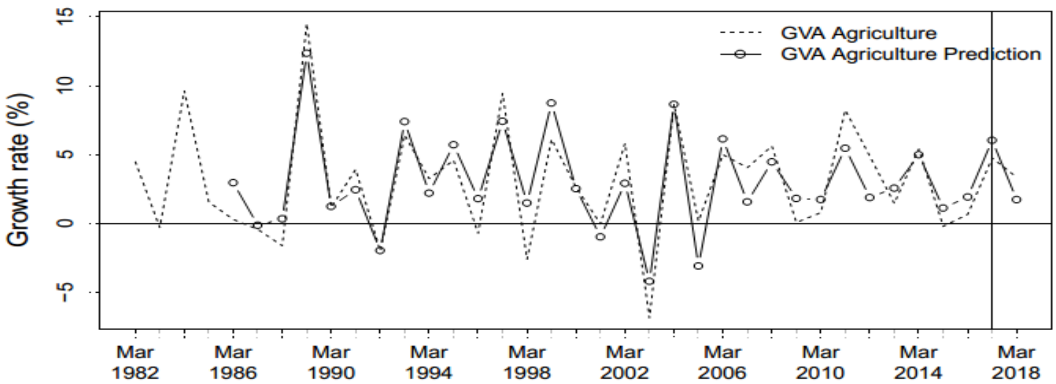
Figure B.1: Agriculture Growth Tracking



(a) Demand Model



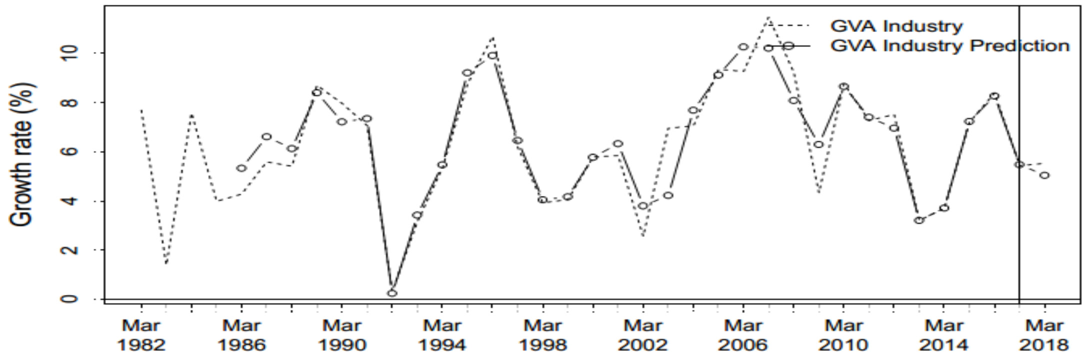
(b) Supply Model



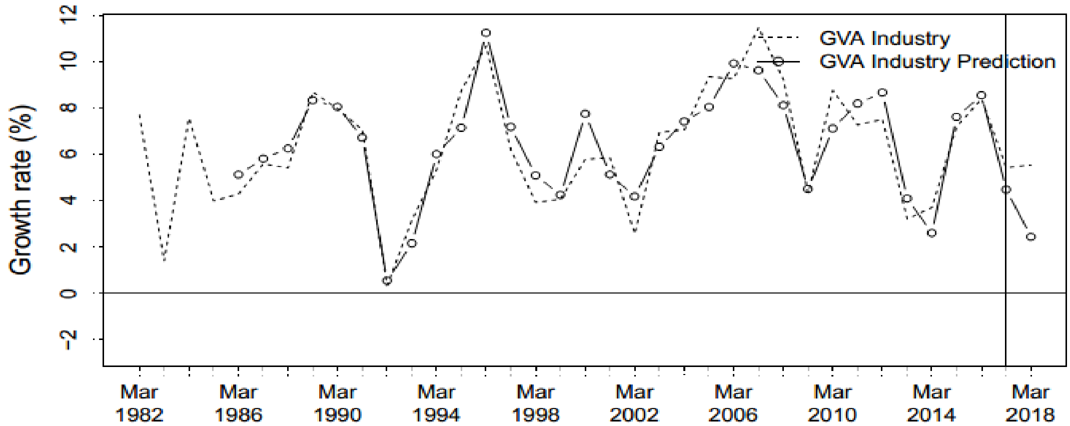
(c) Combined Model

Source: Author's estimation

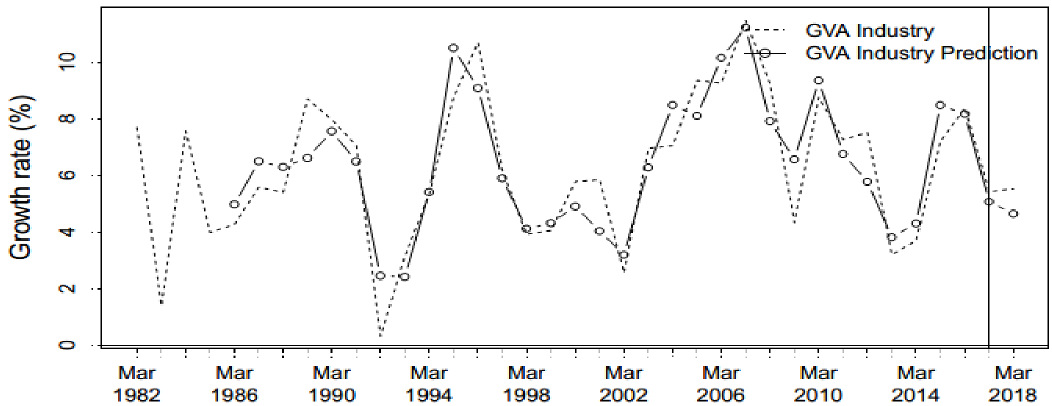
Figure B.2: Industrial Growth Tracking



(a) Demand Model



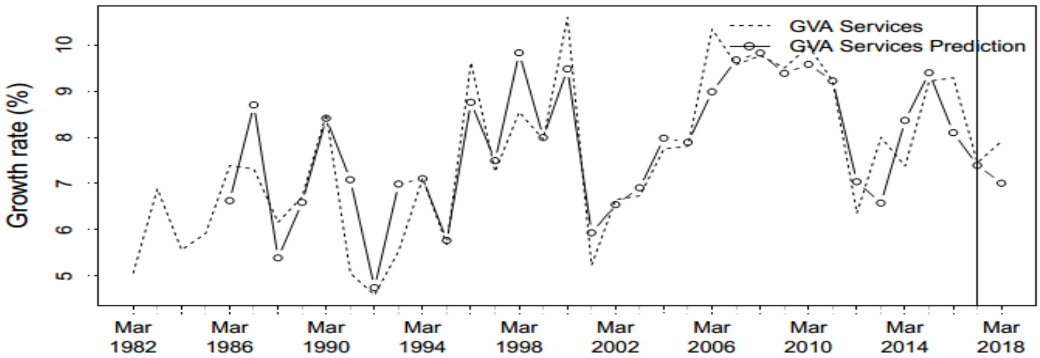
(b) Supply model



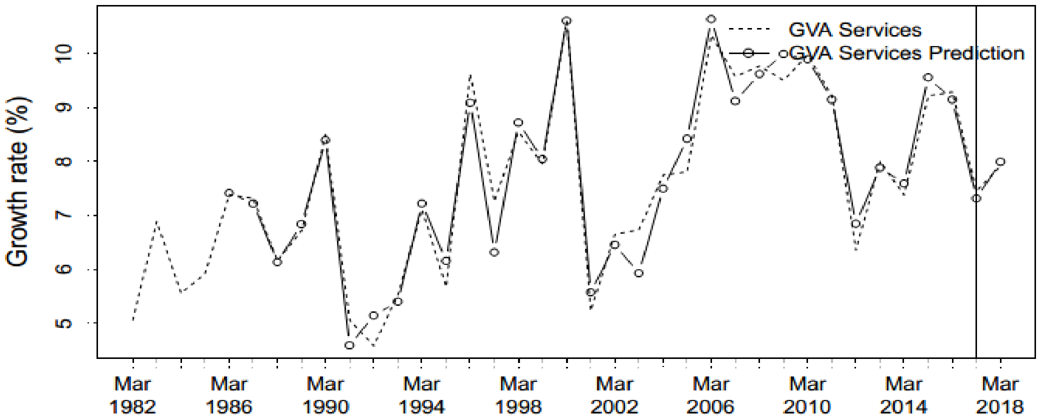
(c) Combined model

Source: Author's estimation

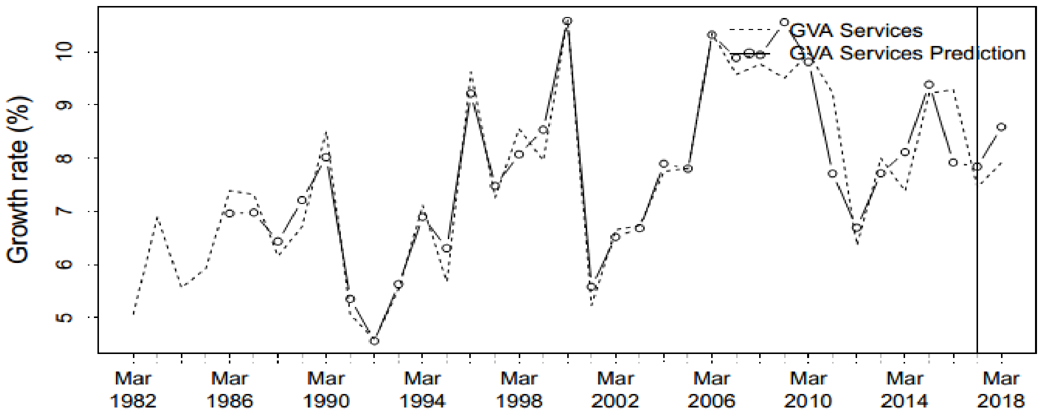
Figure B.3: Services Growth Tracking



(a) Demand model



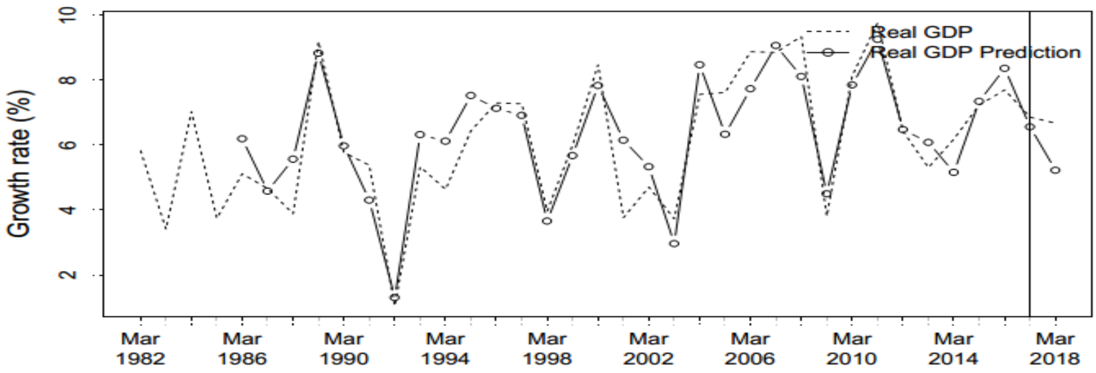
(b) Supply Model



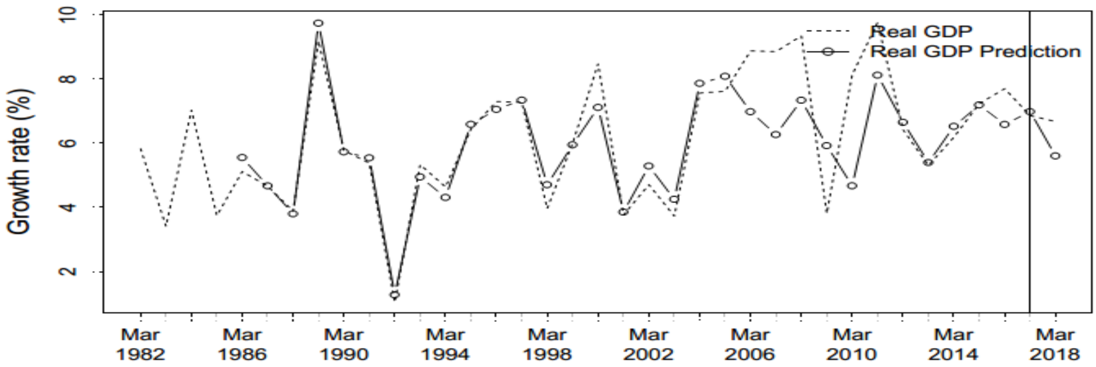
(c) Combined Model

Source: Author's estimation

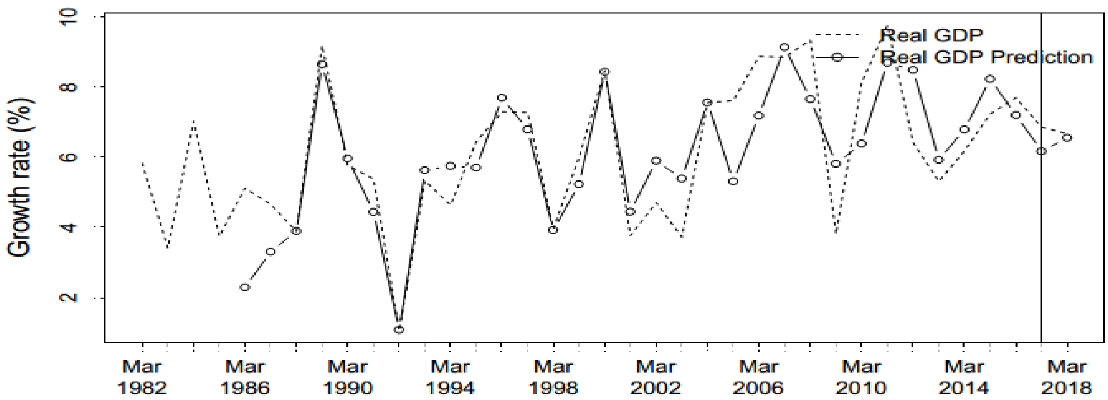
Figure B.4: Real GDP Growth Tracking



(a) Demand Model



(b) Supply Model



(c) Combined Model

Source: Author's estimation

Appendix C

Table C.1: Demand side variables and data sources

Indicators	Source	Unit
Growth Rate of GDP at Market Price (2004-05 prices)	Computed from CSO, Press Releases & Statements, Summary of macroeconomic aggregates at current prices, 1950-51 to 2013-14 and Summary of macroeconomic aggregates at constant (2004-05) prices, 1950-51 to 2013-14.	INR Crore
Growth Rate of GDP at Market Price (2011-12 prices)	Computed from CSO, Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and Constant prices, 2011- 12 series and Growth rates from 2012-13 to 2015-16-Economic survey2015-16,vol-2.	INR Crore
Growth Rate of Agricultural Sector's GDP (2011-12 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004-05 prices and National Ac- counts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011-12) prices (from 2011-12 to 2013-14) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and Constant prices, 2011-12 series (for 2014-15 1st RE)	Per Cent
Growth Rate of Industrial Sector's GDP (2011-12 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004-05 prices and National Ac- counts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011-12) prices (from 2011-12 to 2013-14) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and Constant prices, 2011-12 series (for 2014-15 1st RE)	Per Cent

Growth Rate of Service Sector's GDP (2011-12 prices)	Computed from CSO, National Accounts Statistics Back Series 2011, Statement 5: Gross Domestic Product by economic activity at 2004-05 prices and National Ac- counts Statistics 2015, Statement 1.6: Gross Value Added by economic activity at constant (2011-12) prices (from 2011-12 to 2013-14) and Press Releases & Statements, Annual and Quarterly Estimates of GDP at current and Constant prices, 2011-12 series (for 2014-15 1st RE)	Per Cent
Rate of Gross Capital Formation	National Accounts Statistics 2014, Statement 1: Macro Economic Aggregates (from 1982-83 to 2011-12 at 2004-05 prices) and Economic Survey 2015-16, Table 0.1: Key Indicators) from 2012-13 to 2014-15 at 2011-12 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 2004-05) and National Ac-counts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011-12)	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 2004-05) and National Ac-counts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011-12)	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 2004-05) and National Ac-counts Statistics, 2015, Statement 1.10: Gross Capital Formation by industry of use (at constant prices 2011-12).	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 2013-14 to 2015-16 -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
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 2013-14 to 2015-16 - 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 Ex- change 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 2015-16- Economic Survey 2015-16, 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 (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 C.2: Supply side variables and data sources

Indicators	Source	Unit
Net Capital Stock (At constant (2004-05) 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 (2004-05) prices (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004-05 prices and Statement 22: Net Capital stock by industry of use, National Accounts Statistics 2015	INR Crore
Net Capital Stock in Industry (At constant (2004-05) prices) (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004-05 prices and Statement 22: Net Capital stock by industry of use, National Accounts Statistics 2015	INR Crore
Net Capital Stock in Services (At constant (2004-05) prices) (as on 31st March)	MOSPI, CSO, National Accounts Statistics Back Series 2011, Statement 17: Net Fixed Capital Stock by industry of use at 2004-05 prices and Statement 22: Net Capital stock by industry of use, National Accounts Statistics 2016	INR Crore
Electricity generated	Economic Survey 2015-16, 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 Organised Private Sectors	RBI, Handbook of Statistics, Table 15: Employment in Public and Organised Private Sectors	Million

Employment is computed by adding data on Public and Organised Private Sectors (Due to data non-availability from 2012 to 2013, the data	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 organised sector) employing 10 or more persons.	
Rainfall in India during July	https://data.gov.in/catalog/all-india-area-weighted-monthly-seasonal-and-annual-rainfall-mm	Millimeter
Rainfall in India during December	https://data.gov.in/catalog/all-india-area- weighted-monthly-seasonal-and-annual- rainfall-mm	Millimeter
Rainfall in India during January, February, July, August, September and December	https://data.gov.in/catalog/all-india-area- weighted-monthly-seasonal-and-annual- rainfall-mm	Millimeter

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