

# QUARTERLY FORECASTING MODEL FOR INDIA'S ECONOMIC GROWTH: BAYESIAN VECTOR AUTOREGRESSION APPROACH

*Tara Iyer and Abhijit Sen Gupta*

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## CONTENTS

TABLES AND FIGURES	iv
ABSTRACT	vii
I. INTRODUCTION	1
II. MACROECONOMIC TRENDS IN INDIA	4
III. FRAMEWORK	11
A. Real and Monetary Variables	12
B. Structural Vector Autoregressions	14
C. Forecast Evaluation	15
IV. DATA	15
V. EMPIRICAL RESULTS	17
A. Univariate Autoregressive Integrated Moving Average Models	17
B. Bayesian Vector Autoregressions: Q1 2004–Q1 2017 Estimation Period	18
C. Bayesian Vector Autoregressions: Q1 2011–Q1 2017 Estimation Period	20
D. Vector Autoregression and Structural Vector Autoregression Forecasts	23
E. Extending the Validation Period	24
F. Inflation Forecasts	24
G. The Changing Dynamics of Gross Domestic Product Growth	25
VI. CONCLUSION	26
APPENDIX	28
REFERENCES	37

## TABLES AND FIGURES

### TABLES

1	Real Sector Groups in the Bayesian Vector Autoregressions	13
2	Monetary Sector Groups in the Bayesian Vector Autoregressions	13
3	Structural Vector Autoregression Models	14
4	Empirical Models	16
5	Top 10 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)	18
6	Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2004–Q1 2017 estimation period)	20
7	Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2011–Q1 2017 estimation period)	21
8	Top 10 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)	22
9	Dynamic Bayesian Vector Autoregression and Autoregressive Integrated Moving Average Forecasts of Consumer Price Index Inflation (Q1 2004–Q1 2017 estimation period)	25
10	Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2000–Q4 2006 estimation period)	26
A.1	Data Sources	28
A.2	Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)	30
A.3	Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)	31
A.4	Top 10 Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)	33
A.5	Top 10 Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)	33
A.6	Structural Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)	34
A.7	Structural Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)	34
A.8	Dynamic Bayesian Vector Autoregression and Autoregressive Integrated Moving Average Forecasts of Consumer Price Index Inflation (Q1 2011–Q1 2017 estimation period)	35
A.9	Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2000–Q4 2006 estimation period)	35

### FIGURES

1	Gross Domestic Product Growth	5
2	Decomposition of Gross Domestic Product Growth	5
3	Growth Rate of Key Components of Gross Domestic Product	6
4	Trade Integration	7
5	Export and Import Growth	7
6	Inflation	8
7	Repo and Reverse Repo Rates	9
8	Oil Inflation and Gross Domestic Product Growth	9

9	International Financial Integration	10
10	Portfolio Flows and Foreign Direct Investment	10
11	Effective Exchange Rates	10
12a	Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018)	19
12b	Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018): A Closer Look	19
13a	Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018)	22
13b	Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018): A Closer Look	23
14	5-Quarter Ahead Bayesian Vector Autoregression Forecast	24
15	6-Quarter Ahead Bayesian Vector Autoregression Forecast	24

## ABSTRACT

This study develops a framework to forecast India's gross domestic product growth on a quarterly frequency from 2004 to 2018. The models, which are based on real and monetary sector descriptions of the Indian economy, are estimated using Bayesian vector autoregression (BVAR) techniques. The real sector groups of variables include domestic aggregate demand indicators and foreign variables, while the monetary sector groups specify the underlying inflationary process in terms of the consumer price index (CPI) versus the wholesale price index given India's recent monetary policy regime switch to CPI inflation targeting. The predictive ability of over 3,000 BVAR models is assessed through a set of forecast evaluation statistics and compared with the forecasting accuracy of alternate econometric models including unrestricted and structural VARs. Key findings include that capital flows to India and CPI inflation have high informational content for India's GDP growth. The results of this study provide suggestive evidence that quarterly BVAR models of Indian growth have high predictive ability.

*Keywords:* Bayesian vector autoregressions, GDP growth, India, time series forecasting

*JEL codes:* C11, C32, C53, F43

## I. INTRODUCTION

This study seeks to develop an appropriate forecasting model to predict India's gross domestic product (GDP) growth. It is well known that econometric forecasting has historically been an exercise fraught with uncertainty. The challenge arises in designing a framework that accurately captures the underlying economic structure and the precise variables that provide informational content on the indicators of interest. The forecasting framework should be specific to the country in question, while noting that more complex models with numerous macroeconomic interlinkages often do not perform as well as parsimonious models. Additional econometric challenges arise in developing and emerging market economies (EMEs) since the time series can be more volatile, and sometimes certain variables are unavailable. Yet, precise forecasts are of utmost importance to various stakeholders including policy makers and monetary authorities for whom successful policy decisions depend on accurate predictions. This paper develops an econometric framework that is effective in predicting GDP growth in India.

We construct a quarterly forecasting framework employing key macroeconomic variables based on economic theory on the real and monetary sectors in the economy. Bayesian vector autoregression (BVAR) models have been known to generate reasonable forecasts (e.g., Giannone et al. 2015) and address the curse of dimensionality that arises with unrestricted VARs. By specifying a prior distribution for the parameters of the VAR model and using Bayes' theorem, Bayesian inference allows for more efficient estimates and forecasts without as much of a loss of degrees of freedom. We corroborate the BVAR models in this study with structural vector autoregressions (SVARs), where identification restrictions are imposed based on economic theory. VAR and autoregressive integrated moving average (ARIMA) models of GDP growth are also estimated. We select the most effective GDP growth forecasting model based on estimating and evaluating the predictive ability of several multivariate econometric models that capture key macroeconomic linkages in the Indian economy.

In the BVARs, we specify four real sector models of GDP growth and three models that describe monetary policy. These are discussed further in section III. The real sector variable groups are based on aggregate demand indicators including public and private consumption, and external sector variables such as foreign direct investment (FDI) and portfolio flows. We also assess the effects of the exchange rate on growth since India is open to trade and financial flows. The monetary sector variable groups are specified in terms of the underlying inflationary process. Noting that the Reserve Bank of India (RBI) switched to consumer price index (CPI) inflation targeting in 2015 from a hitherto multiple indicators approach where wholesale price index (WPI) inflation was a target, we test models specified in the CPI as well as in the WPI using the repo rate as the monetary policy instrument. Given the predominance of cash-based economic activity in India, we assess variants of these models with money, and specify some BVARs only in narrow money. We further control for the effects of oil price shocks and United States (US) monetary policy.

A key finding is that the BVAR models are able to predict the dynamics of GDP growth very well. A large number of BVAR models are estimated over the first quarter of 2004 until the first quarter of 2017, with their out-of-sample forecast accuracy evaluated over the latest four quarters for which data is available. The best BVAR forecasts are shown to closely track the data (Figures 8a and 8b in section V), and outperform ARIMA, VAR, and SVAR models. The significant majority of BVAR models developed in this paper outperform a random walk forecast, the conventional benchmark used in the literature. The results from estimating the BVARs suggest that the models that perform the best take into account the influence of global factors, such as FDI and portfolio flows, in driving GDP growth in India.



The high predictive power of the BVARs holds robust to major shocks such as the global financial crisis (GFC) and the Indian demonetization, structural changes including the monetary policy regime switch from a multiple indicators approach to inflation targeting, revisions in the Indian national accounts data, as well as several variations in the start and length of the estimation and validation periods. In the BVARs, tighter prior distributions seem to allow for greater forecast accuracy than looser beliefs. Further, spot oil prices and CPI inflation seem to have predictive content for GDP growth. Additional findings include that the BVARs have good predictive power for CPI inflation as well, a useful finding from the standpoint of the literature. Another finding from estimating the models over a historical time period is that the variables relevant for predicting GDP growth seem to have changed over time, with trade linkages more relevant in the early 2000s, and capital flows highly influential from 2005 onward.

## Literature Review

The literature contains several forecasting studies for EMEs in general, and some previous papers on India. For the most part, macroeconomic indicators in emerging markets are not found to be easy to predict, with random walk models sometimes found to outperform more complex econometric frameworks. Bayesian and factor-augmented VARs, however, seem to perform relatively well. Two recent papers, Mandalinci (2017) and Duncan and Martinez-Garcia (2018), compare and summarize the results of multivariate VAR-based forecasting models across several EMEs.

Mandalinci (2017) compares the forecasting performance of various time series specifications for a panel of 10 EMEs from Q1 2001 to Q3 2014. The models include univariate as well as multivariate VAR frameworks for inflation and GDP such as factor-augmented VARs (FAVAR), time-varying parameter VARs (TVPVAR), and unobserved component stochastic volatility (UCSV) specifications. They find that overall the UCSV model performs the best across countries (especially in Mexico and Turkey) followed by the TVPVAR specification. During the peak of the GFC, however, the TVPVAR performed better. For India, a time-varying parameter factor-augmented VAR (TFP-FAVAR) is found to perform reasonably well along with the UCSV specification.

Duncan and Martinez-Garcia (2018) analyze the predictive ability of quarterly inflation forecasting models over the years 1980–2016 for 14 EMEs. A variant of the random walk model is generally found to be the best framework for predicting inflation. The authors contrast these results for EMEs with those for advanced economies, where variants of the Philips curve specification have found more success in forecasting inflation (evidence based on studies including Coibion and Gorodnichenko 2015 and Kabukçuoğlu, and Martínez-García 2018). Apart from random walk types of specifications for forecasting inflation, factor-augmented models also tend to perform relatively better.

While the studies above analyze the performance of forecasting models across a panel of EMEs, we also review some papers that assess the predictive ability of models for individual countries. Liu and Gupta (2007) develop a dynamic stochastic general equilibrium (DSGE) model to forecast South African macroeconomic aggregates including gross national product and investment at a quarterly frequency from 1970 to 2000. They compare the predictive ability of the DSGE model to a range of VAR and BVAR models. They find that, in general, the DSGE model performs relatively poorly and that BVAR specifications perform the best. Among the BVAR models, those with looser priors outperform the others in terms of predicating consumption and investment, whereas the predictability of gross national product improves with tighter Bayesian priors. In follow-up papers, Gupta and Kabundi (2010, 2011), in forecasting key macroeconomic aggregates in South Africa, find that large-

scale dynamic factor models (DFMs) and BVARs have better predictive ability than structural DSGE models or reduced-form VAR specifications.

Altug and Cakmakli (2016) formulate an inflation forecasting model based on inflation expectations measured using survey data for two EMEs—Brazil and Turkey. The baseline model treats inflation as a random walk process with a seasonal component. Survey-based expectations are brought into the model by assuming that survey and model-predicted expectations match each other save for a random error. The model is estimated at a quarterly frequency from 2001 to 2014 to find that a forecasting model augmented with survey-based expectations does no worse than a moving average model in Brazil, and in Turkey has superior predictive ability. Öğünç et al. (2013) and Gunay (2018) evaluate the forecasting properties of a range of models including BVARs and FAVARs in Turkey, to find that factor models do not always have greater predictive power despite utilizing more data.

Öğünç et al. (2013) forecast inflation at a quarterly frequency for Turkey for a time period from 2001 onward using a variety of models including ARIMAs, VARs, BVARs, and FAVARs. They find that forecast averaging works the best, in general, in terms of reducing prediction error. Gunay (2018) analyzes the ability of different factor models to predict industrial production and inflation in Turkey at a monthly frequency from 2009 onward. The model uses data on industrial production, trade, interest and exchange rates, commodity prices, financial market indicators, and consumer and business confidence. The predictive ability of factor models depends on their specification and the particular data series used in generating the factor. Doğan and Midiliç (2016) employ more than 200 daily financial series, including commodity prices and equity indices, to forecast and nowcast quarterly GDP in Turkey using mixed data sampling techniques. The authors find that the use of high-frequency financial and macroeconomic data in predicting output leads to forecasting gains.

Figueiredo (2010) analyzes the ability of FAVAR models to predict inflation in Brazil at a monthly frequency from 1995 to 2009, after the Real Plan stabilization program started in 1994. To construct the factor model, they employ nearly 400 variables on prices, labor market indicators, aggregate and sectoral output, interest rates, and other monetary and financial market indicators, and trade related indicators. The study finds that using more factors does not necessarily increase predictive accuracy, and that the relative performance of factor models improves with longer forecast horizons. Pincheira, Selaive, and Nolzco (2017) develop a time series model to predict headline inflation in eight developing countries in Latin America on a monthly basis from 1995 to 2017. The methodology developed focuses on whether core inflation has any useful informational content in predicting headline inflation in a multivariate single-equation regression model for CPI inflation. The findings indicate that core inflation generally improves the predictive ability of the CPI model when the forecast horizon is less than 6 months.

Deryugina and Ponomarenko (2014) develop a BVAR model to forecast key Russian Federation macroeconomic indicators at a quarterly frequency from 2000 to 2013. They include 14 variables in the framework ranging from real sector variables (GDP, consumption, investment) to prices (including the CPI and GDP deflator), to monetary variables (including broad money and loans to households), and external variables (including oil prices). They find that although the BVAR model has relatively better predictive ability for real sector variables, it is outperformed by a random walk specification in most cases. Porshakov et al. (2015) seek to predict Russian Federation GDP using a DFM with many macroeconomic and financial variables. The paper focuses on short-term forecasts, nowcasts, and backcasts on a quarterly basis. Findings include that while modeling fewer variables produces adequate nowcasts and backcasts, the predictive accuracy of the DFM for one-quarter ahead and two-quarter ahead GDP increases with the number of factors.

Some papers exist in the literature that seek to forecast industrial production or economic growth in India. Aye, Dua, and Gupta (2015) evaluate the performance of 11 forecasting models for India. They collect 15 monthly series from 1997 to 2011 on domestic and foreign industrial production, the WPI, Treasury bill yields of different maturities, London interbank offered rates of different maturities, public expenditure, money, and the exchange rate. While GDP growth is not included in the model, various VARs, BVARs, and factor models are used to predict four variables—industrial production, inflation, the exchange rate, and the 3-month Treasury bill rate. A key result from this paper is that while the models generally outperform a random walk specification, the out-of-sample predictions from the suite of VARs, BVARs, and factor models are far off from tracking the data. Benes et al. (2017) develop a semistructural model for the purposes of generating policy simulations for the Indian economy but they do not provide evaluations of the model’s ability to generate adequate forecasts.

In an earlier study on India, Biswas, Singh, and Sinha (2010) forecast industrial production, WPI inflation, and narrow money using quarterly data from 1994 to 2007 using VAR and BVAR approaches. The one-step ahead BVAR forecasts are able to reasonably track historical data, but dynamic forecasts are not provided. Bhattacharya, Chakravarti, and Mundle (2018) use a factor-augmented time-varying parameter regression approach to forecast India’s GDP growth. While the model is able to capture historical trends in growth quite well, this is based on static forecasts similar to Biswas, Singh, and Sinha (2010). Furthermore, the model is estimated at an annual frequency. The present study makes two contributions to the literature. First, we are perhaps the first to use a Bayesian VAR approach to forecast economic growth in India on a quarterly basis. We evaluate dynamic forecasts, which are relevant to stakeholders, with our dataset extending until 2018. We compare the BVAR forecasts to that of VARs, SVARs, and ARIMAs. Second, we develop a macroeconomic framework that models the real and monetary sides of the Indian economy. This approach yields novel insights into the predictive ability of various real and monetary theories of economic growth in India.

The rest of this paper is structured as follows. Section II provides an overview of some key macroeconomic trends in India. Section III develops the BVAR forecasting framework and discusses the real and monetary models that we specify of the Indian economy. Section IV discusses the data used in the empirical analysis. Section V presents the empirical results and evaluates the predictive ability of the models. Section VI concludes.

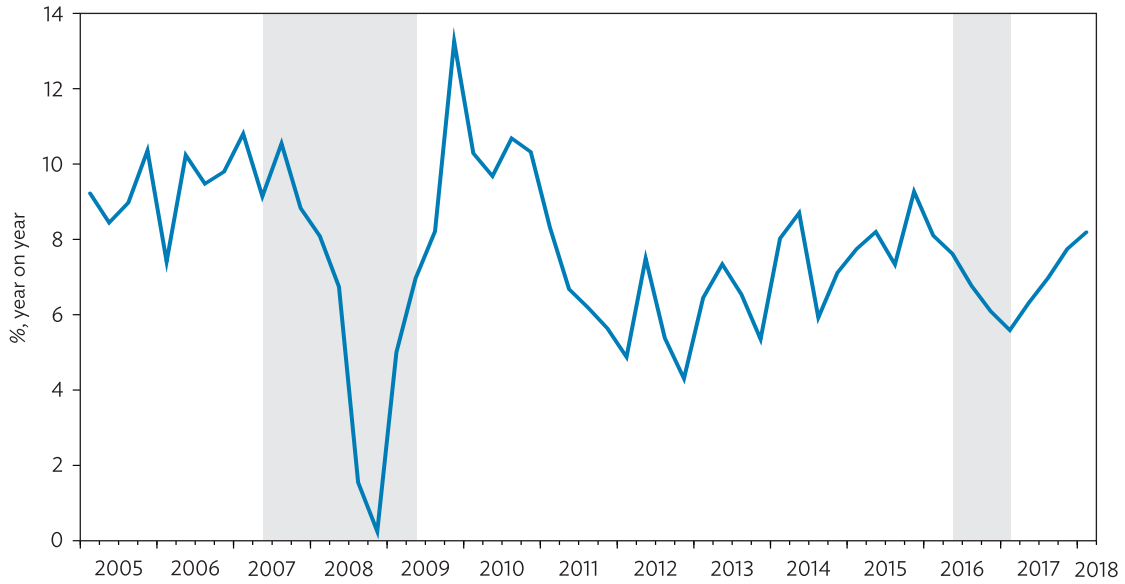
## II. MACROECONOMIC TRENDS IN INDIA

India has emerged as one of the fastest-growing emerging economies, growing at an average rate of 7.6% during the last decade and a half (Figure 1). This paper tracks India’s growth process from Q1 2004 onward to build a quarterly model that captures the main determinants of economic growth.<sup>1</sup> India’s GDP grew by an average of 5.5% between Q1 1997 and Q4 2003, primarily driven by domestic demand comprising private consumption and investment (Figure 2). GDP growth surged between Q1 2004 and Q2 2008, with the average growth rate exceeding 9%, before growth declined during the GFC. While private consumption and investment continued to remain key drivers of growth due to significant domestic reforms, exports also became an important contributor owing to favorable external factors, which included a surge of capital flows to emerging markets including India (for further details, see World Bank 2018).

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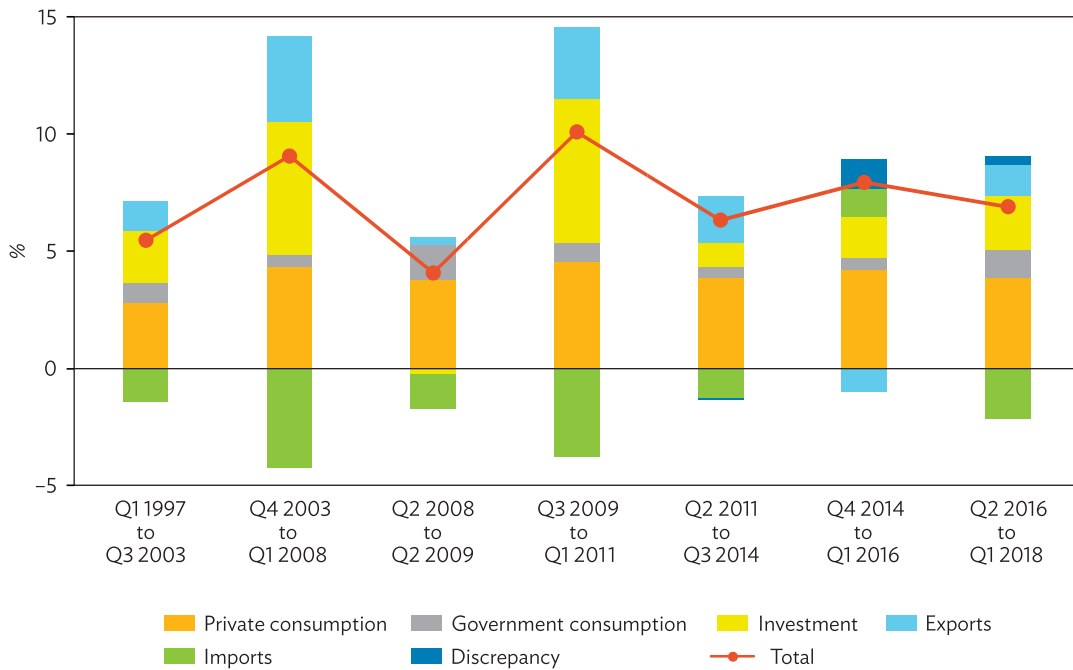
<sup>1</sup> Quarterly data on Indian GDP is available from Q2 1996. Furthermore, all dates in this paper are in the Indian fiscal year format (April 1 – March 31), so that, for instance, Q1 1996 refers to the April 1 – June 30 quarter.

Figure 1: Gross Domestic Product Growth



Source: Centre for Monitoring Indian Economy (CMIE) Economic Outlook Database (accessed 15 December 2018).

Figure 2: Decomposition of Gross Domestic Product Growth

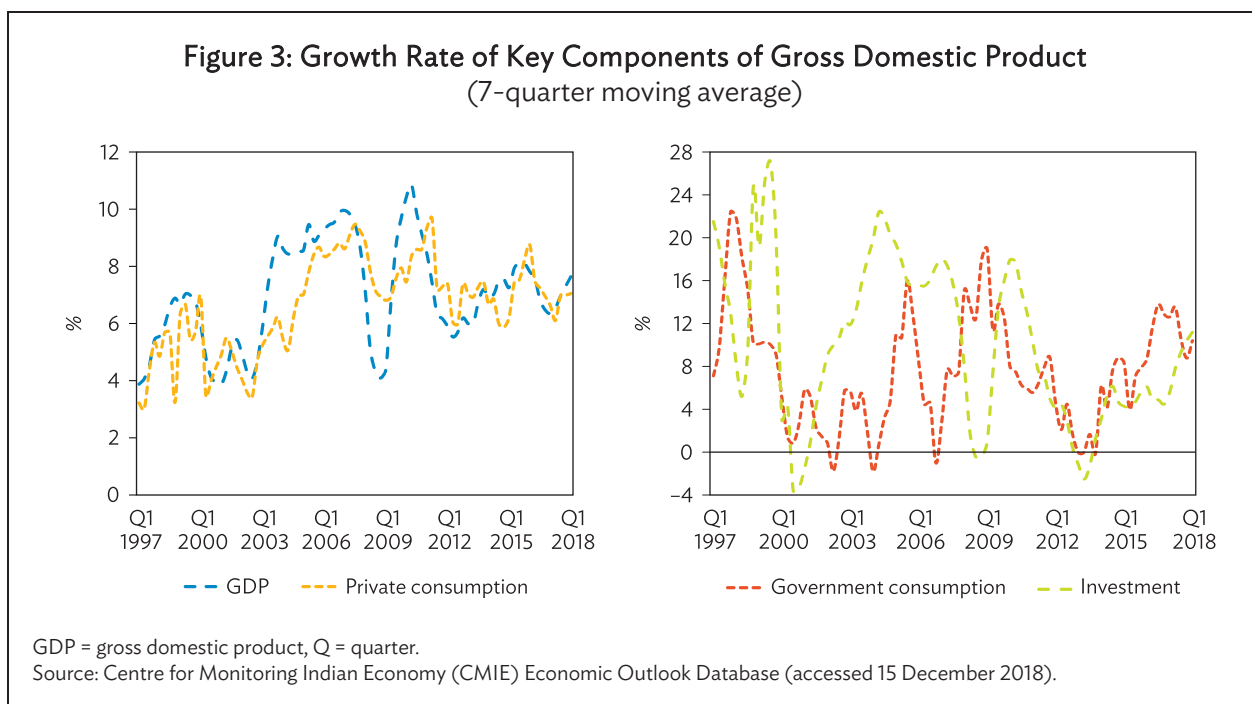


Q = quarter.

Source: Centre for Monitoring Indian Economy (CMIE) Economic Outlook Database (accessed 15 December 2018).

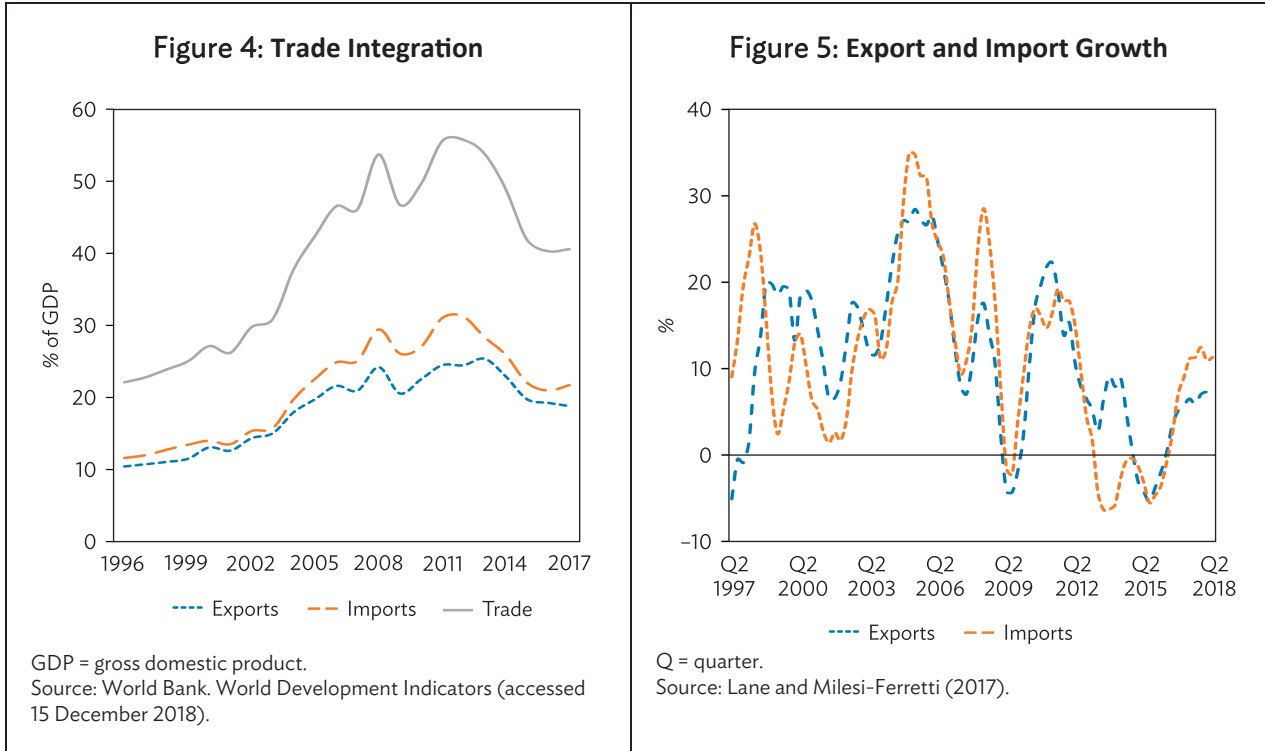
India's GDP growth has witnessed a lot of volatility in the subsequent period. GDP growth slowed significantly in the wake of the GFC, with growth dropping to an average of 4.1% during Q3 2008 to Q3 2009. Growth was largely consumption led in this period with private and government consumption accounting for a major part of the growth with the government providing a large fiscal stimulus. Exports and investment remained virtually stagnant over this period. India recovered relatively fast from the GFC and growth rebounded to average over 10% during Q4 2009 to Q2 2011 aided by a pickup in investment and exports. However, emerging policy and structural bottlenecks, along with external factors becoming less benign, resulted in growth dropping to an average of 6.3% during Q3 2011 to Q4 2014. Growth recovered somewhat to 8% in the period Q1 2015 to Q2 2016, as India, being one of the largest crude oil importers, benefitted from a sharp drop in global oil prices along with resolution of some of the bottlenecks. Cash shortages in the aftermath of demonetization, firms incurring transitional costs post the introduction of the goods and services tax (GST) and a recovery in global oil prices resulted in growth dipping down to 6.9% in the most recent period.<sup>2</sup>

Private consumption expenditure has remained the single largest component of GDP, accounting between 52.2% and 65.7% of GDP. Along with government consumption, whose growth has been much more volatile, over all consumption has accounted between 68.2% and 78.7% of GDP. Investment growth has also been very volatile. Healthy growth in the period prior to the GFC led to investment reaching nearly 40% of GDP. However, investment growth slowed down markedly since then owing to structural and policy bottlenecks, heightened uncertainty and deteriorating business confidence. While there has been some recovery in recent quarters, investment growth has lagged GDP growth resulting in the investment-to-GDP ratio declining to 34.5% by Q1 2018.



<sup>2</sup> On 8 November 2016, the government withdrew the legal tender status of INR500 and INR1,000 currency notes, which accounted for 86% of the value of cash in circulation and introduced new INR500 and INR2,000 notes. The delay in the printing of the new notes led to a cash shortage and temporarily strained economic activity. The GST was introduced from 1 July 2017, replacing a plethora of central, state, and interstate taxes with a single nationwide tax. Some uncertainty related to the structure, rates, and exemptions had a transitional impact on business activity.

India has become more integrated with the global economy over the past few decades. India's trade integration, measured as a share of exports and imports to GDP, increased from around 20% of GDP in the late 1990s to over 55% in mid-2008 (Figure 4). Much of the increase was witnessed between 2003 and 2008 when exports grew by 23.1% annually while imports grew by 30.2% (Figure 5). With the slowdown in global trade since 2011, structural bottlenecks hampering the domestic manufacturing sector and a decline in commodity prices, both exports and imports experienced growth that trailed GDP growth, resulting in the ratio of trade to GDP dropping to around 40.6% in recent quarters.

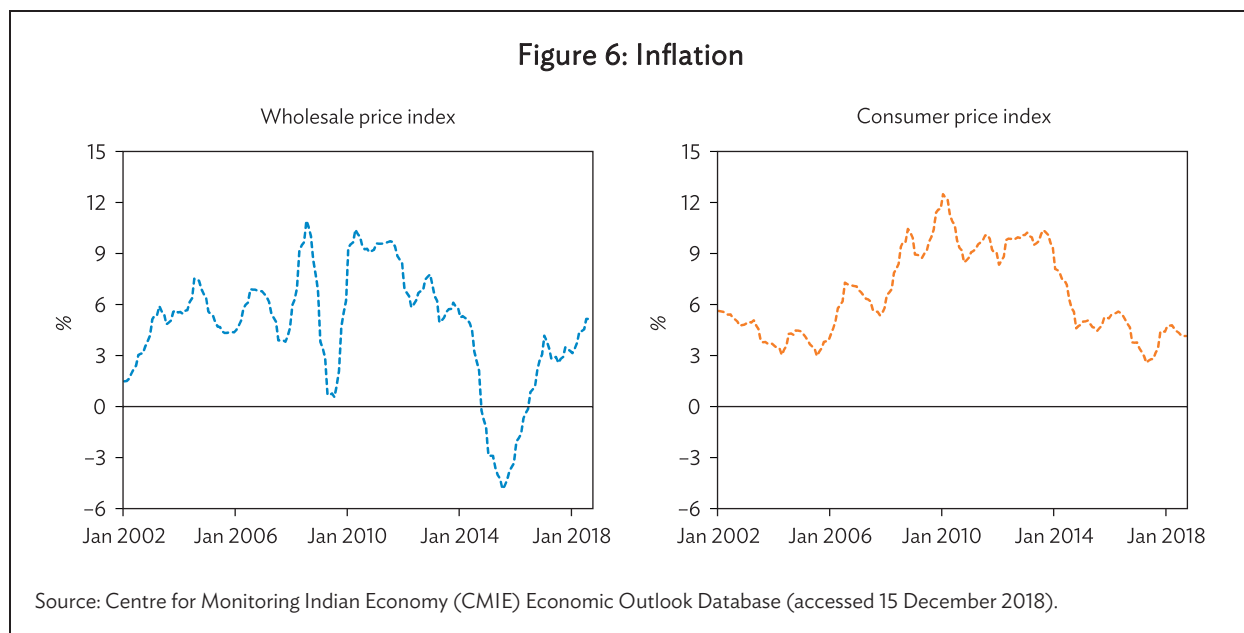


Inflationary pressures impact GDP growth. In India, inflation is measured using a wide range of indices. The two most commonly used indices to track inflation are the CPI and WPI. The WPI measures the prices of goods at different stages in the production and distribution process while the CPI measures the retail prices of goods and services that households consume. In India there are four different types of CPI inflation depending upon the different segment of the population they focus on. These include industrial worker, agricultural labor, rural labor, and urban nonmanual employees. Since 2011, the government started releasing data on a new measure of CPI known as Combined CPI, which provides price indices separately for rural and urban population. This is a more representative measure as it includes the service sector, which accounts for the largest share of India's GDP. Both WPI and CPI price indices are available at a monthly frequency. Finally, the GDP deflator is another index that can be used to measure inflation. The GDP deflator is obtained by using different primary price indices, which are used to deflate individual components of GDP valued at current prices to obtain volume estimates. However, as pointed out in Patnaik, Shah, and Veronese (2011) in India, the GDP deflator is mainly available at a quarterly frequency and for selected products.

Given the wider coverage and greater representation by the Combined CPI index, and the fact that Combined CPI inflation has been selected as the official target under the Monetary Policy Framework Agreement signed in February 2016, we focus on Combined CPI inflation in this paper.



However, data on Combined CPI inflation is available only from 2012. To overcome this, we follow RBI (2014) and use the backcast data generated by using CPI-Industrial Worker (Base: 2001=100).

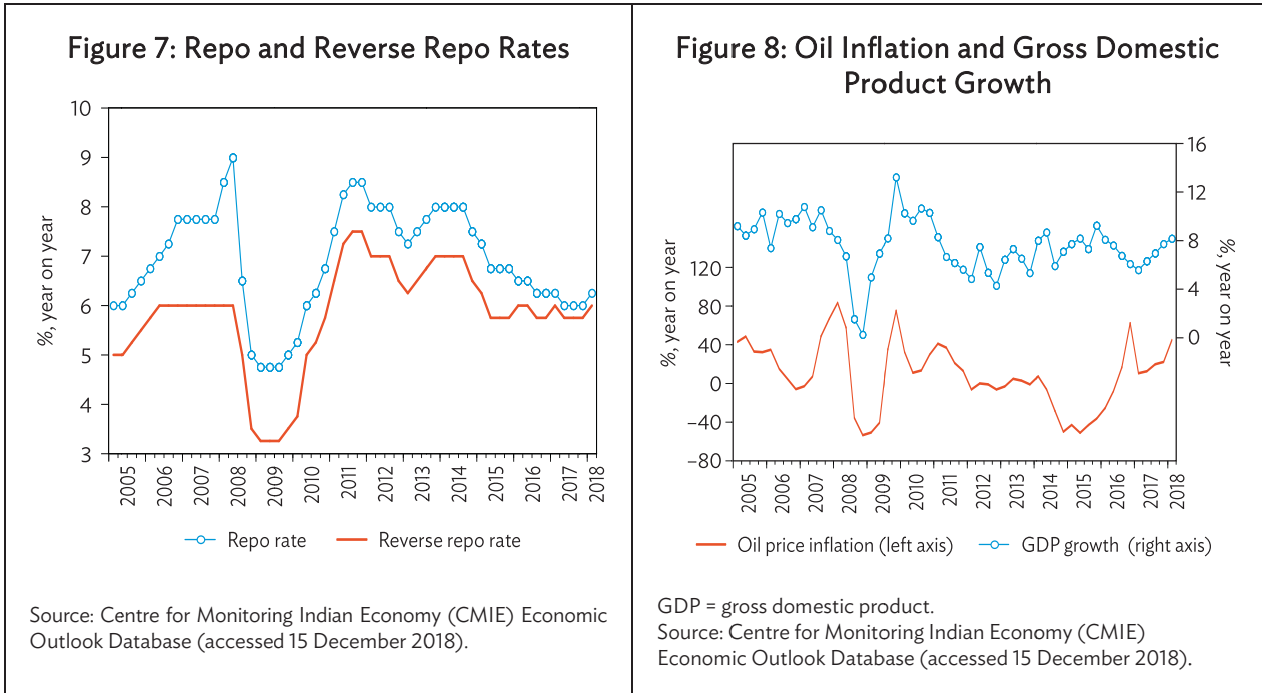


There are fundamental differences between the WPI and Combined CPI, especially in the weights of the various components. The share of food and beverages in the Combined CPI basket is 45.9%, nearly double of the 24.4% weight accorded in the WPI basket. In contrast, fuel and light account for only 6.8% in the Combined CPI while its share in the WPI is 13.2%. Finally, manufactured goods continue to dominate the WPI with a share of 64.2% while goods and services account for 47.3% in the Combined CPI inflation. As a result of these differences the CPI and WPI have moved in different directions (Figure 6). In the immediate period before the GFC, both the WPI and CPI inflation witnessed an increase, although the extent of increase in the case of WPI inflation was much higher. This was primarily due to a rise in global fuel and food prices, which also impacted domestic food prices. WPI inflation fell sharply during the GFC since iron and steel prices contracted by 20% and fuel prices contracted by 10%. The dip lasted for a few months only as commodity prices recovered shortly. CPI inflation continued to increase driven by domestic factors such as high procurement prices and rising demand for high-value food products (Bajpai 2011, Bhattacharya and Sen Gupta 2017). CPI inflation, despite dipping from the peak reached in late 2009 remained at elevated levels until late 2013, mainly due to high food prices even though WPI inflation dipped on account of moderation in commodity prices.

A combination of factors caused both the WPI and the CPI inflation to decline since 2014. These include food inflation remaining low due to improved food management, modest increase in procurement prices and benign global prices. A sharp drop in global commodity prices including crude oil prices and the introduction of inflation targeting led to a moderation in core and fuel inflation. Again, the decline in the WPI inflation was more pronounced due to the sharp drop in crude oil prices, impacting fuel inflation, which had a higher weight in the WPI basket. Shocks such as demonetization also contributed to low inflation during this period as it temporarily disrupted economic activity. Inflation started inching up from mid-2017 as growth picked up and crude oil prices rebounded sharply.

The monetary policy architecture has also undergone significant changes since the late 1990s. In 1998, the RBI adopted a “multiple indicators approach,” wherein various macroeconomic indicators, including various rates of return, exchange rate, credit extended by financial institutions, fiscal position, trade and capital flows, and inflation rate were analyzed to underline monetary policy perspectives. This multiple indicator approach was further augmented with forward looking indicators drawn from various surveys. To improve the monetary policy operating framework, a Liquidity Adjustment Facility was set up in 2000 under which the RBI uses the repo and the reverse repo rates as key policy instruments providing a corridor for the overnight money market rates (Figure 7). The width of the corridor has differed over time depending on the macroeconomic needs of the economy.

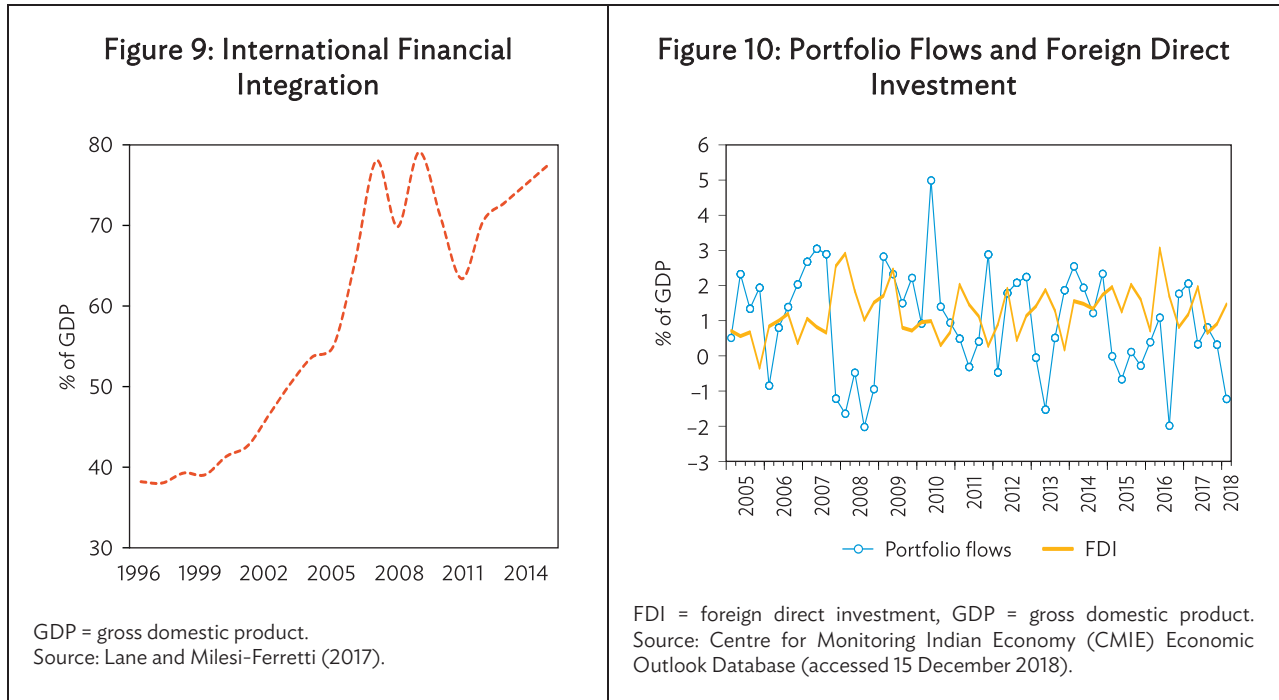
Oil prices and economic activity in India appear to be fairly correlated with an  $R^2$  of 0.43 for the entire period i.e., Q1 2004 to Q1 2018 (Figure 8). The oil price index is modeled in this paper as an exogenous variable. The correlation is seen to be significantly higher in the period encompassing the GFC until before the oil price collapse in 2014 with the  $R^2$  rising to 0.69 during Q1 2008 to Q4 2013. This high positive correlation is likely spurious and was possibly driven by common global shocks including the GFC, the subsequent recovery, and the eurozone crisis. In recent years, the correlation between oil prices and GDP has veered toward the negative side (the correlation from Q1 2014 to Q1 2018 is  $-0.32$ ), probably because of fewer common global shocks. Furthermore, an increase in global oil prices results in a negative terms of trade shock, given India’s high import dependence, resulting in a decline in GDP growth as resources that could be domestically invested or consumed are transferred outside. Similarly, a decline in global oil prices is likely to benefit economic growth.



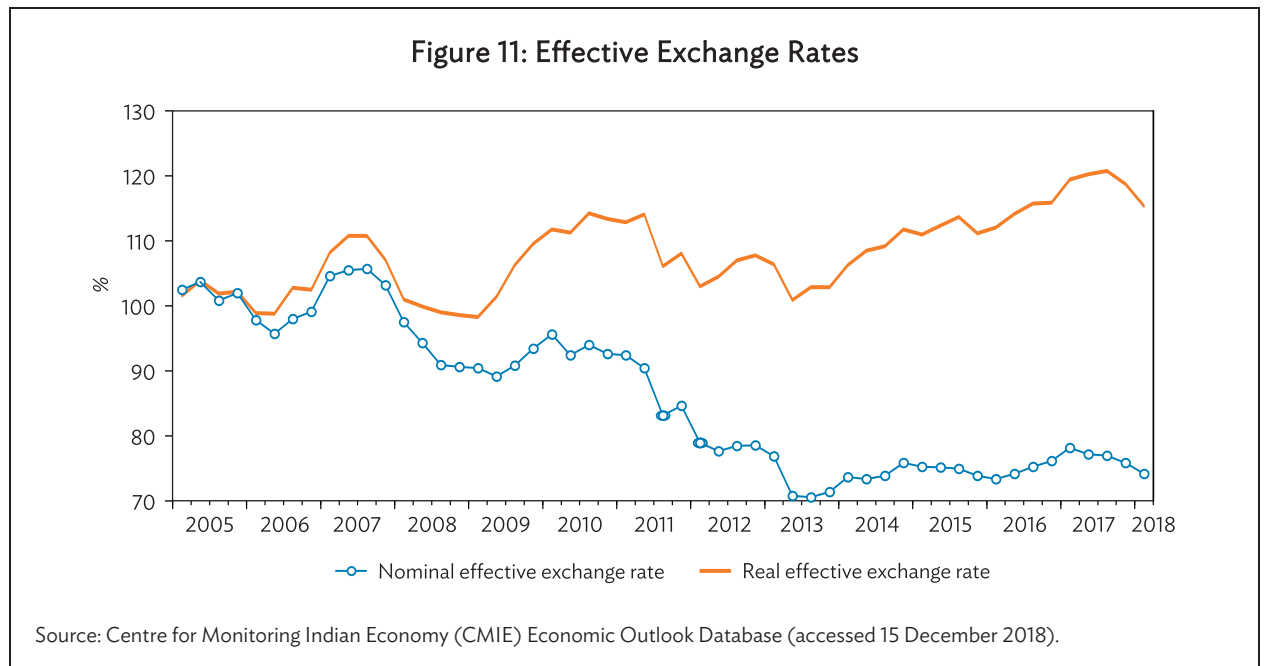
In line with its rising trade openness, India has also become significantly integrated with global capital markets. According to Lane and Milesi-Ferretti (2017), India’s integration with the global capital markets, measured as the ratio of foreign assets and foreign liabilities to GDP increased from less than 40% in the late 1990s to over 75% in recent years (Figure 9). Much of this increase has been driven by a surge in portfolio and FDI flows, which was aided by India undertaking a graded liberalization of capital flows (Figure 10). Equity flows were given preference over debt flows, and within equity flows



FDI was preferred compared to portfolio flows. Portfolio flows are seen to be generally more volatile than FDI. Portfolio flows played a role in increasing growth prior to the GFC but reversed as growth slowed down in the aftermath. Capital flows to India slowed again during the taper tantrum of 2013, when US Treasury yields surged as the Federal Reserve slowed down its quantitative easing program.



Given India's rising integration with global markets, both on the current and financial account, the exchange rate has emerged as a key variable for economic growth. Figure 11 plots the trade-weighted nominal effective exchange rate (NEER) and real effective exchange rate (REER). The NEER is a summary measure of



the rate at which the rupee trades against a basket of currencies of 36 of India's trading partners. The REER is the nominal exchange rate adjusted for price differentials between India and these trading partners.

Since the GFC, NEER, and REER have followed divergent path (Figure 10). The NEER has depreciated over time indicating that the Indian rupee has weakened against these currencies. However, despite the weakening in nominal terms, the rupee has appreciated in real terms against this basket of currencies since inflation in India continue to remain higher compared to most trading partners.

### III. FRAMEWORK

In this section, we outline the framework and methods we use for the purposes of forecasting GDP growth. Let  $Y_t$  be a vector of  $N$  endogenous variables

$$Y_t = \mu + \beta_1 Y_{t-1} + \dots + \beta_k Y_{t-k} + u_t$$

where  $\mu$  is a vector of constant terms,  $\beta_1, \dots, \beta_k$  are coefficient matrices, and  $u_t$  is an error component that is normally distributed with a mean set of zeroes and covariance matrix  $\Sigma$ ,  $u_t \sim N(0, \Sigma)$ . If we consider an unrestricted VAR model for  $Y_t$ , then the distribution of the parameter vector  $\beta \equiv \text{vec}([\mu, \beta_1, \dots, \beta_k]')$  can be computed through ordinary least squares. An essential part of the macroeconomic toolkit, VARs capture the dynamic interdependencies among variables.

An unrestricted VAR allows the data to “speak” by imposing minimal assumptions on the data and removing any constraints arising from economic theory. One drawback, however, is that the estimates are inefficient if the VAR is overparameterized. Increasing the number of parameters and lags in a VAR can lead to an exponential reduction in degrees of freedom. Overparameterization, besides inducing inefficient VAR estimates, can also lead to large forecast errors (Aye, Dua, and Gupta 2015). The BVAR approach, proposed in Litterman (1986), provides a solution to the VAR problem of overparameterization.

Consider the following conditional prior distribution of the VAR coefficients

$$\beta | \Sigma \sim N(b, \Sigma \otimes \Omega \lambda)$$

where the vector  $b$  is the prior mean of the coefficients of each equation,  $\Sigma \otimes \Omega \lambda$  is the covariance matrix with  $\lambda$  as a scalar parameter governing the tightness of the prior distribution and  $\Omega$  as a matrix of known weights, and the vector of hyperparameters,  $\xi$ , determines the properties of the specified prior distribution. The prior distribution characterizes the uncertainty associated with estimating the parameters of the model before observing the variables. The BVAR parameters are random variables with probability distributions in contrast to the VAR model, where the parameters are not stochastic. The posterior distribution of the parameter vector,  $\beta | \Sigma, y$ , derived by combining the prior distribution with the likelihood function, is normally distributed in many cases and given by

$$\beta | \Sigma, y \sim N(\hat{\beta}(\xi), \hat{V}(\xi))$$

$$\hat{\beta}(\lambda) \equiv \text{vec}(\hat{B}(\xi))$$

$$\hat{B}(\xi) \equiv (X'X + (\Omega\xi)^{-1})^{-1}(X'Y + (\Omega\lambda)^{-1}v)$$

$$\hat{V}(\xi) \equiv \Sigma \otimes (X'X + (\Omega\lambda)^{-1})^{-1}$$

where  $Y \equiv [Y_{k+1}, \dots, Y_T]'$ ,  $X \equiv [X_{k+1}, \dots, X_T]'$ ,  $X_t \equiv [1, Y'_{t-1}, \dots, Y'_{t-k}]'$ , and  $\nu$  is a matrix whose rows correspond to the prior mean of the coefficients of each equation (see Giannone, Lenza, and Primiceri [2015] for further details). The posterior distribution reflects that the prior distribution is updated based on Bayes' Theorem using the likelihood function, which represents the information contained in the data about the parameters of the VAR model. Using maximum likelihood estimation, we employ two commonly used conjugate prior distributions for which it is possible to derive analytical expressions for the posterior distributions: the Minnesota prior and the normal-Wishart prior.

The Minnesota prior on  $\beta$  is normally distributed conditional on the variance-covariance matrix,  $\Sigma$ , of error terms. This matrix is estimated by estimating the complete variance-covariance matrix implied by the VAR, with a degrees of freedom correction. There are four main hyperparameters in the Minnesota prior distribution:  $\lambda, \mu, \gamma, \sigma$ .  $\lambda$ , perhaps the most important hyperparameter, controls the prior standard deviation of the parameters and should be set closer to 0 for a tighter prior distribution. We vary  $\lambda$  between 0.1 and 0.5 to assess the forecasting accuracy of a more restrictive versus looser prior distribution.  $\mu$ , the prior on the first-order autoregressive coefficient, is typically set at or close to 1 if the model is specified in levels to take into account persistence in the time series, and at 0 if the data in the model is in growth rates and stationary. We set  $\mu$  at 0.  $\gamma$ , a cross-variable specific variance parameter that lies between 0 and 1 (lower values reduce or turn off the coefficients of cross-lag variables), is set at 0.99 to allow cross-lag variables to play a greater role in the estimation process.  $\sigma$  influences the rate at which the coefficients on higher-order lags are shrunk toward 0, and we set it at 1 for no lag decay.

We also estimate the BVARs based on a normal-Wishart prior distribution for the parameters. While the Minnesota prior does not take into account any uncertainty in the estimation of the variance-covariance matrix of error terms,  $\Sigma$ , the normal-Wishart prior models this uncertainty by estimating the complete variance-covariance matrix with Bayesian methods. This yields a posterior distribution for the parameters that is the product of normal and Wishart distributions. For further details on the Minnesota and normal distributions, see Miranda-Agrippino and Ricco (2018). The prior distribution for the estimation of the normal-Wishart matrix  $\Sigma$  is set to depend on two hyperparameters,  $\zeta$  and  $\nu$ , where  $\zeta$  represents the prior degrees of freedom and  $\nu$  is an identity matrix. Two hyperparameters govern the prior distribution of the parameter vector:  $\lambda$  and  $\mu$ . These have the same interpretations as with the Minnesota prior.  $\mu$  is set at 0 as the model is specified in growth rates, and we vary the hyperparameter,  $\lambda$ , between 0.1 and 0.5 to assess how the tightness of the prior distribution influences forecasting accuracy.

## A. Real and Monetary Variables

Each BVAR model in this study includes variables from the real and monetary sectors. We specify four real models of GDP growth and three models that describe the evolution of monetary policy. The first real sector group of variables, which follows in the Keynesian tradition, allows output to be determined by the traditional drivers of aggregate demand: government spending, private consumption, investment, and the trade balance. Termed the Keynesian Demand (KD) model, we empirically assess several variants of this, and the other three models as detailed in the next section. The second variable group, which we term the Exchange Rate Consumption (EC) model, accounts for the effects on growth of the dynamic interlinkages between domestic consumption, the major component of GDP, and international relative prices (captured through the trade-weighted exchange rate). Since exchange rate volatility impacts consumption patterns in developing countries that depend on traded goods (e.g., Iyer 2016, Cravino and Levchenko 2017) and since the effects on GDP of domestic consumption is typically reinforced by

corresponding fluctuations in international relative prices in open economies, it is interesting to test whether the consumption–exchange rate nexus can explain the dynamics of output growth.

The third and fourth real sector groups of variables assess the importance of international financial integration and capital flows for predicting economic activity in India. FDI and portfolio inflows can enhance growth by reducing credit constraints in developing countries, augmenting investment resources, increasing capital allocation and efficiency, enhancing domestic finance sectors, and providing beneficial learning effects through technology transfer (e.g., Kawai and Takagi 2008, Hannan 2018). Capital inflows can also adversely impact growth by increasing the possibility of sudden stops in international lending and causing resources to transfer from tradable to slower-growing nontradable sectors (e.g., Calvo and Reinhart 2000, Gourinchas and Obstfeld 2012, Reis 2013). The Global Factors (GF) model assesses whether international financial integration and capital flows influence GDP growth in India. Finally, the Fiscal External Flows (FEF) model examines whether the confluence of government outlays and international investment has predictive power for economic growth. Table 1 summarizes the real sector models of growth.

**Table 1: Real Sector Groups in the Bayesian Vector Autoregressions**

Real Sector Groups	Variables
Keynesian Demand (KD)	GDP, government spending, private consumption, investment, net exports
Exchange Rate Consumption (EC)	GDP, effective exchange rate, government spending, private consumption
Global Factors (GF)	GDP, portfolio flows, FDI flows
Fiscal External Flows (FEF)	GDP, government spending, portfolio flows, FDI flows

FDI = foreign direct investment, GDP = gross domestic product.

Source: Authors' compilation.

We specify the monetary theories in terms of the underlying inflationary process. The RBI institutionalized a “multiple indicators” approach from the early 2000s, where there was no explicit intermediate target. A variety of economic indicators were targeted, and the particular measure of inflation was based on the WPI. With the signing of the Monetary Policy Framework Agreement in 2015, a regime of flexible inflation targeting was formally adopted with CPI inflation as the target. The repo rate has been the primary instrument to implement monetary policy since the Liquidity Adjustment Facility was set up in 2000. We set up models with CPI inflation and the repo rate, and WPI inflation and the repo rate. Since India is predominantly a cash-based economy with a high share of informal market transactions, we test variants of these models with money (M1) included in the spirit of the quantity theory of money. We finally assess a model with only money to see whether changes in the monetary base has an impact on output due to capacity constraints in the short run. These monetary theories are summarized in Table 2.

**Table 2: Monetary Sector Groups in the Bayesian Vector Autoregressions**

Inflationary Process	Variables
CPI Inflation	CPI and repo rate (plus a version with money)
WPI Inflation	WPI and repo rate (plus a version with money)
Money	Monetary base (narrow money)

CPI = consumer price index, WPI = wholesale price index.

Source: Authors' compilation.

## B. Structural Vector Autoregressions

We pair the Bayesian analysis with SVARs. SVARs are based on an underlying economic structure specified by the researcher. The SVAR disturbance terms are serially uncorrelated, achieved by placing restrictions on the contemporaneous correlations in an unrestricted VAR. The SVAR residuals,  $\varepsilon_t$ , and the reduced-form errors,  $u_t$ , are related through

$$\varepsilon_t = Bu_t$$

where we impose identification restrictions on the parameters in the matrix  $B$ . In this study, we work with a 4-variable VAR in GDP, inflation (WPI or CPI), money, and the repo rate. We include the spot oil price index and the Federal Funds rate as exogenous variables, assuming that the former is an exogenous global shock and the latter affects global business cycles (Rey 2015).

The identification scheme assumes that domestic monetary policy shocks do not affect output and inflation within the same quarter. Inflation reacts to output with a lag. The equation for inflation can be interpreted as an aggregate supply equation, and that for output as an aggregate demand equation. The equation for money demand can be interpreted as being derived from the quantity theory of money,  $MV = PY$ . The repo rate is ordered last, as monetary policy is set after observing the current values of money, output, and inflation. The recursive identification scheme is given below.

$$\begin{bmatrix} \varepsilon_t^{inf} \\ \varepsilon_t^{gdp} \\ \varepsilon_t^{m1} \\ \varepsilon_t^{rep} \end{bmatrix} = \begin{bmatrix} b_{11} & 0 & 0 & 0 \\ b_{21} & b_{22} & 0 & 0 \\ b_{31} & b_{32} & b_{33} & 0 \\ b_{41} & b_{42} & b_{43} & b_{44} \end{bmatrix} \begin{bmatrix} u_t^{inf} \\ u_t^{gdp} \\ u_t^{m1} \\ u_t^{rep} \end{bmatrix}$$

We also assess variants of the baseline identification scheme to run four unique identification schemes, and 16 SVARs totally. The baseline SVAR is specified without exogenous variables, and three more sets are specified using as exogenous controls the spot oil price index, the Federal Funds rate, and oil prices and the Federal Funds rate together. The variables are specified in stationary terms (year-on-year growth rates), where we denote GDP by *gdp*, CPI or WPI inflation by *cpi\_inf* or *wpi\_inf*, narrow money by *m1*, and the repo rate by *rep*, the oil price index by *oil*, and the Federal Funds rate by *ff*. The identification restrictions for the four models without exogenous variables are found below in Table 3.

**Table 3: Structural Vector Autoregression Models**

Model 1	{cpi_inf, gdp, m1, rep}
Model 2	{cpi_inf, gdp, rep}
Model 3	{wpi_inf, gdp, m1, rep}
Model 4	{wpi_inf, gdp, rep}

CPI\_inf = consumer price index inflation, GDP = gross domestic product, m1 = narrow money, rep = repo rate, WPI\_inf = wholesale price index inflation.

Source: Authors' compilation.

### C. Forecast Evaluation

Each model's predictive ability is evaluated by splitting the sample into two portions—the estimation period and the validation period. The estimation period consists of observations  $[T_0, N]$ . In the estimation period, each model is estimated and used to generate forecasts for  $N + h$ , where  $h = 1, 2, \dots, T_1$  is the forecast horizon. In the validation period, consisting of observations  $[N + 1, T_1]$ , we evaluate the out-of-sample predictive accuracy of different models: BVARs, SVARs, VARs, and ARIMAs. To evaluate each forecast, the root mean squared forecast error (RMSFE) of each model is analyzed, where

$$RMSFE = \frac{1}{T_1} \sum_{h=1}^{T_1} (v_{t+h|t})^2$$

for  $v_t$  as any model's forecast error. The multivariate model forecasts are compared to the forecast from a random walk as standard in the literature. For a model to beat the random walk, the RMSFE of that model relative to the random walk, or the *relative* RMSFE, is required to be lower than 1. Along with the RMSFE of each model, we also provide the mean absolute forecast error, and the Theil U inequality coefficient which lies between 0 and 1 (values closer to 0 indicate greater forecasting accuracy).

## IV. DATA

We specify the models based on time series of a quarterly frequency. The dataset extends from the first quarter of 2000 until the latest available time period, which, at the time of writing, is the first quarter of 2018. The two main estimation samples used in this study to generate four-quarter ahead out-of-sample forecasts begin in Q1 2004 and Q1 2011, with both ending in Q1 2017. We also investigate the changing dynamics of GDP growth by analyzing the four-quarter ahead predictions from an earlier estimation sample extending from Q1 2000 to Q1 2006. Of note is that the fiscal year in India begins on April 1 and ends on March 31 of the following year. The first quarter of each year in our dataset therefore extends from April until June, and the last quarter extends from January until March. We draw the variables from several databases including the Indian Ministry of Statistics and Programme Implementation, the RBI, and the Federal Reserve Economic Database maintained by the Federal Reserve Bank of St. Louis. A complete description of data sources is provided in Table A.1 in the Appendix.

The data are in constant price terms with base year 2011–2012. A few years ago, the Central Statistics Office released a new series of national accounts in 2011–2012 prices. This series was rebased from the previously used 2004–2005 national accounts series and adjusted methodologically to take into account the changing nature of economic activity over time. For further details on the 2011–2012 price series, please see NSC (2018). Since our dataset tracks back until 2000 with some series specified in 2004–2005 prices, we splice the data so that all series are in constant 2011–2012 prices. For the CPI, since these data are only available from the fourth quarter of 2010, we backcast the series using the reweighted industrial CPI. For the NEER and the REER, we use the 36-currency trade-weighted indices from 2004 onward. Since these variables are only available from the first quarter of 2004 we splice the 36-currency indices with the reweighted 6-currency indices from 2000 to 2004.



We test the time series for stationarity using the augmented Dickey–Fuller and Phillips–Perron unit root tests. The data series in levels are found to be nonstationary, and since we are interested in a stationary forecasting model, we transform the variables into year-on-year growth rates to eliminate unit roots. Once transformed, the variables in differences are stationary. As discussed in section III, we empirically assess 14 real models and seven monetary theories of Indian growth in the data. We control for oil price shocks and the effects of US monetary policy by including oil prices and the Federal Funds rate as exogenous variables. The seven monetary models can be classified into three broad categories as in Table 2: in CPI inflation, WPI inflation, and the monetary base. We test variants of these model using the repo rate as the instrument of monetary policy, and accounting for money given the predominantly cash-based nature of economic activity in India.

**Table 4: Empirical Models**

Real Variables		Monetary Variables		
<b>GF</b>	GF1: GDP, FDI/GDP	Model 1	CPI, repo rate	
	GF2: GDP, portfolio flows/GDP	Model 2	CPI, money	
	GF3: GDP, FDI/GDP, portfolio flows/GDP	Model 3	CPI, repo rate, money	
<b>EC</b>	EC1: GDP, NEER, private consumption, government spending	Model 4	WPI, repo rate	
	EC2: GDP, REER, private consumption, government spending	Model 5	WPI, money	
	EC3: GDP, NEER, government spending	Model 6	WPI, repo rate, money	
	EC4: GDP, REER, government spending	Model 7	Money	
<b>FEF</b>	FEF1: GDP, government spending, FDI/GDP		Exogenous Variables	
	FEF2: GDP, government spending, portfolio flows/GDP			Spot oil price
	FEF3: GDP, government spending, FDI/GDP, portfolio flows/ GDP			Federal Funds rate
<b>KD</b>	KD1: GDP, private consumption, government spending, investment		Spot oil price, Federal Funds rate	
	KD2: GDP, private consumption, government spending, investment, net exports			
	KD3: GDP, government spending, investment			
	KD4: GDP, government spending, investment, net exports			

CPI = consumer price index, EC = exchange rate consumption, FDI = foreign direct investment, FEF = fiscal external flows, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, NEER = nominal effective exchange rate, REER = real effective exchange rate, WPI = wholesale price index.

Source: Authors' compilation.

The endogenous variables in the real and monetary models, along with the exogenous control variables, are detailed in Table 4 above. The 14 groups of real variables can be classified into four broad categories as in Table 1. These four economic theories of the real side of the economy examine the influence of domestic and external factors in predicting GDP growth. The KD model tests whether aggregate demand indicators matter for predicting GDP growth. The EC model accounts for the importance of public and private expenditure in economic activity, and the role of international relative prices in influencing domestic consumption and growth. The GF model assesses whether international financial integration and capital flows influence output growth. Finally, the FEF model tests whether the confluence of fiscal activity and cross-border capital flows matter for forecasting growth.

## V. EMPIRICAL RESULTS

We estimate the forecasting models over two main samples. In the first estimation, the sample period begins in the first quarter of 2004. This is around the time when GDP growth in India began to accelerate, and India started becoming more integrated with the global economy. For robustness, we also vary the start of the first estimation period to the first quarters of 2005 and 2006 for robustness checks. In the second estimation, the sample period begins in the first quarter of 2011. While in the first estimation the sample period includes the GFC and 2010 eurozone debt crisis, the second estimation period excludes these. It is useful to have a second estimation period as several major structural changes in India have taken place over the past few years including the shift to an inflation targeting framework from a multiple indicators approach, demonetization of high currency notes, and the introduction of the GST. Moreover, as shown in Figure 2, the drivers of growth have varied markedly over time so using results from a more recent estimation period would provide additional insights. The start of the second estimation period also corresponds to the time when the Central Statistics Office revised and rebased the Indian national accounts data.

Both estimation periods end in the first quarter of 2017, with the forecast horizon set to be four quarters ahead. We are interested in dynamic forecasts, where the previously forecasted values are used to compute future predictions. In contrast, static forecasts use actual data to compute one-step ahead predictions. Since the dynamic approach significantly increases forecast errors relative to the static approach, the former method is a more rigorous test of whether a model has adequate predictive power. We assess the predictive ability of univariate ARIMA models before turning to the richer multivariate frameworks fitted through SVARs and BVARs. The validation period, over which the predictive ability of the models is tested, extends from the second quarter of 2017 until the first quarter of 2018. The forecasting power of different models is assessed using the RMSFE statistic. As conventional in the literature, we compare the RMSFE of various models with that of a benchmark random walk growth forecast. We also compare the out-of-sample accuracy of the BVAR and SVAR forecasts to that of unrestricted VARs.

### A. Univariate Autoregressive Integrated Moving Average Models

As a first step before the Bayesian multivariate approach, we follow the Box–Jenkins procedure (Box et al. 2015) for selecting the best univariate ARIMA forecasting model. The GDP series is first made stationary by taking its year-on-year growth rate. We then examine its autocorrelation and partial autocorrelation functions to pick a preliminary ARIMA model for each estimation period. If the estimated coefficients are not significant, or if the residuals are not white noise, we respecify the model. Evidence of white noise is checked through autocorrelation and partial autocorrelation plots of the residuals, as well as a portmanteau Box–Pierce test with the null hypothesis that the residuals are white noise. Through this iterative process, we develop the optimal ARIMA models for each of the two estimation periods. The forecasting power of these univariate models is compared to a random walk forecast. The results suggest that for the estimation period starting in Q1 2004, a univariate model of growth with 2 autoregressive (AR) terms and 1 moving-average (MA) term yields a relative RMSFE (RRMSFE) of 0.11, and for the estimation period starting in Q1 2011, a univariate model of growth with 3 AR terms and 2 MA term yields an RRMSFE of 0.26. While the univariate specifications compare favorably with the random walk benchmark (the RRMSFEs are well below 1), these models are much further off from tracking Indian growth dynamics than the BVARs, as discussed next.



## B. Bayesian Vector Autoregressions: Q1 2004–Q1 2017 Estimation Period

We use a Bayesian approach to estimate the multivariate models. We estimate each of the seven monetary models independently before repeating the exercise with the 14 real models and three sets of exogenous driving factors—(i) oil prices, (ii) the Federal Funds rate, and (iii) oil prices and the Federal Funds rate. We run each BVAR with looser prior beliefs on the parameters ( $\lambda = 0.5$ ) as well as with tighter priors ( $\lambda = 0.1$ ). This accords with the literature, where hyperparameters for the optimal forecast are typically chosen based on the predictive ability of alternate Bayesian specifications. While tighter priors can limit the data from “speaking” as much, overfitting may be a concern with looser beliefs. We use the Minnesota and normal-Wishart prior distributions. For the Minnesota distribution, the initial residual covariance matrix is estimated through a VAR with a degrees of freedom correction.

Overall, as detailed in Table 4, we fit 420 unique BVAR models of GDP growth based on the real and monetary approaches. These include all the combinations of 15 real sector groups (the 14 real models outlined in Table 4 plus a baseline real model specified only in GDP), 7 monetary models, and 4 sets of exogenous variables (oil, Fed Funds, oil and Fed Funds, no controls). Each model is estimated with four sets of priors to make for a total of 1,680 BVAR models for each estimation period. We also test the significance of recent structural changes to monetary policy—the adoption of inflation targeting in the first quarter of 2015 and the demonetization shock in the third quarter of 2016.

Table 5 displays the top 10 BVAR forecasting models with the corresponding RRMSFEs, root mean absolute forecast errors (RMAFEs) or the MAFE relative to the random walk, and the Theil U coefficient. Of note is that these models are able to track the data very closely in the out-of-sample dynamic forecasts, shown in Figure 12a and zoomed in further in Figure 12b. The specifications hold robust when we vary the start of the estimation period to a year and 2 years ahead. The monetary policy specification with CPI inflation as the target and the repo rate as the instrument comprises 70% of the top 10 forecasting models. Most of these models are also based on the normal-Wishart tight prior. We also check whether models other than the top 10 are able to accurately predict GDP growth. We find that several BVAR models are able to generate very good forecasts. The top 50 models with corresponding forecast evaluation statistics can be found in Table A.2 in the Appendix.

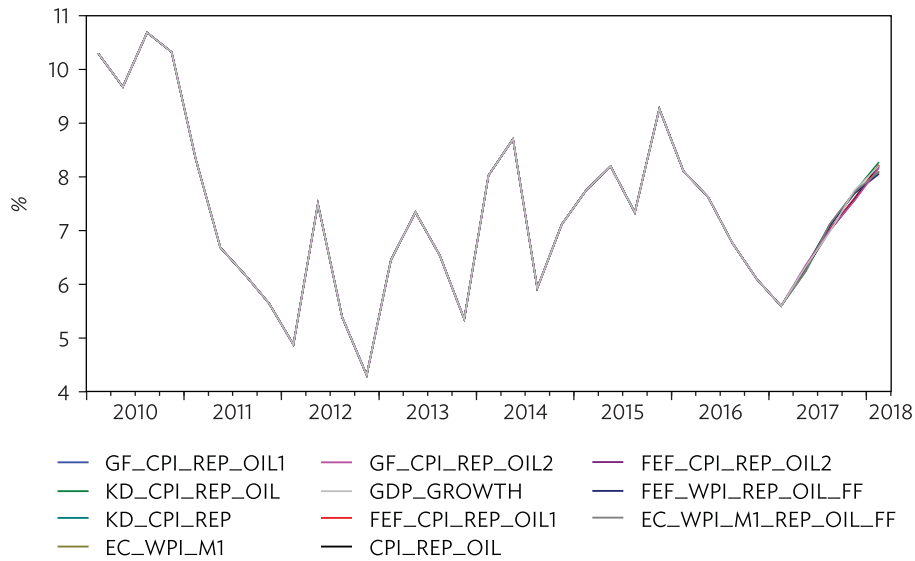
**Table 5: Top 10 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMFSE	RMAFE	Theil U
1	GF2	CPI, REP	OILS	Norm Tight	0.011	0.008	0.005
2	FEF2	CPI, REP	OILS	Norm Tight	0.011	0.009	0.006
3	KD4	CPI, REP	OILS	Norm Tight	0.011	0.011	0.006
4	...	CPI, REP	OILS	Norm Tight	0.012	0.008	0.006
5	KD4	CPI, REP	...	Minn Loose	0.013	0.011	0.006
6	FEF3	CPI, REP	OILS	Norm Tight	0.013	0.008	0.006
7	EC3	WPI, M1	...	Norm Loose	0.013	0.011	0.007
8	FEF1	WPI, REP	OILS, FF	Minn Loose	0.013	0.011	0.007
9	GF3	CPI, REP	OILS	Norm Tight	0.014	0.010	0.007
10	EC1	WPI, M1, REP	OILS, FF	Norm Loose	0.014	0.013	0.007

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMFSE = relative root mean squared forecast error, WPI = wholesale price index.

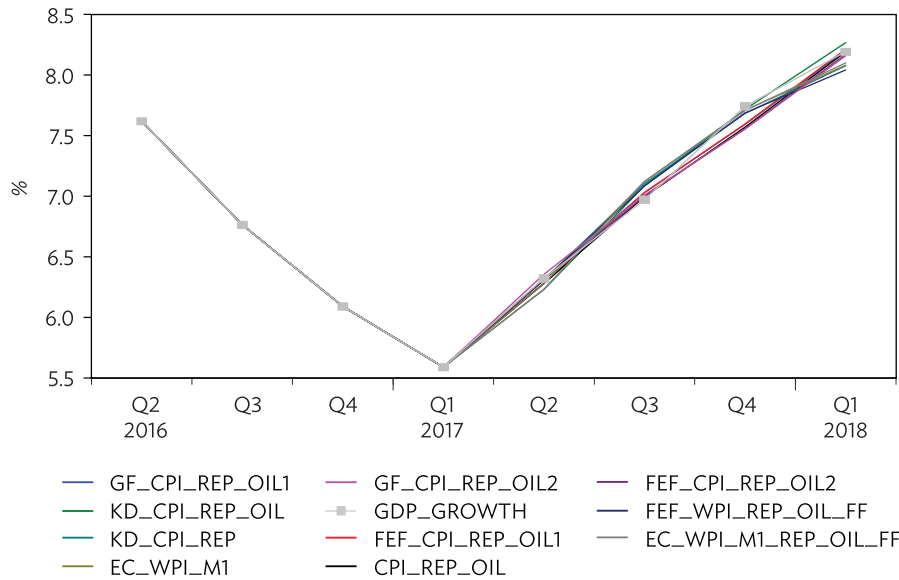
Source: Authors' calculations.

Figure 12a: Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018)



CPI = consumer price index, EC = exchange rate consumption, FDI = foreign direct investment, FEF = fiscal external flows, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, NEER = nominal effective exchange rate, Q = quarter, REER = real effective exchange rate, REP = repo rate, WPI = wholesale price index.  
 Note: Q1 2004–Q1 2017 is the estimation period.  
 Source: Authors' calculations.

Figure 12b: Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018): A Closer Look



CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, WPI = wholesale price index.  
 Notes: Q1 2004–Q1 2017 is the estimation period. This is a zoomed in version of Figure 12a.  
 Source: Authors' calculations.

Of the top 50 BVAR models, we find that 18 models are specified in CPI inflation (either with the repo rate, or the repo rate and money) and 32 models are specified in WPI inflation (either with the repo rate, money, or the repo rate and money). Thus, while the CPI inflation specification of monetary policy prevails in the top 10 models, the WPI inflation specification seems to be a more important predictor of growth overall. Of note is that in these BVAR models of Indian macroeconomic aggregates, 28 models are based on the normal-Wishart tight prior, and 22 are based on looser priors (either normal-Wishart or Minnesota). In terms of the exogenous control variables, the spot oil price index appears in 26 models alone, and in 12 models with the Federal Funds rate. Over the estimation period starting in 2004, US monetary policy seems to matter less than oil prices for predicting economic activity in India.

**Table 6: Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2004–Q1 2017 estimation period)**

Real	Monetary	Exogenous	Priors
16 GF	14 CPI, REP	26 OIL	28 Norm Tight
12 FEF	4 CPI, M1, REP	12 OIL, FF	11 Norm Loose
10 KD	12 WPI, M1, REP	4 FF	11 Minn Loose
6 EC	11 WPI, M1	8 NONE	
6 Mon	9 WPI, REP		

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, WPI = wholesale price index.

Source: Authors' calculations.

An interesting finding is that the GF model of the real side of the economy appears to be among the better predictors of GDP growth. Sixteen of the top 50 models are based on the GF specification, with the FEF model coming second with 12 of the top 50 BVAR models. The KD model comes third followed by the EC model. These findings indicate that FDI and portfolio flows seem to matter significantly for predicting the dynamics of GDP growth. This seems intuitive given the significant increase in India's international financial integration over the past few decades as discussed in section II. Much of this increase has been driven by a surge in portfolio and FDI flows, which was aided by India undertaking a graded liberalization of capital flows. Table 6 above provides further details on the composition of the top 50 BVAR forecasting models.

### C. Bayesian Vector Autoregressions: Q1 2011–Q1 2017 Estimation Period

We estimate the 1,680 BVAR models again over the Q1 2012–Q1 2017 sample to find that the real sector specifications are similarly ranked in terms of predicting GDP growth, as found in Table 7. The GF and FEF comprise 15 and 10 models, respectively of the top 50 models. Now, however, the CPI specification of the inflationary process dominates the top 10 models (all are in the CPI) as well as the top 50 models (42 are in the CPI and only 8 are in the WPI). Further, 29 of the top 50 models have the monetary policy specification in CPI inflation, the repo rate, and money. The high predictive power of this particular model is fairly intuitive since CPI inflation was adopted as the target for monetary policy in 2015 (whereas WPI inflation had been one of the key variables considered for monetary policy for much of the 2004–2017 estimation period). Money possibly gains more importance in the shorter estimation period due to the demonetization shock, which eradicated 86% of the currency in circulation and was correlated with a sharp drop in economic activity.

We can see that the spot oil price index has lost predictive power in the shorter and more recent estimation period, and that the Federal Funds rate plays more of a role now. This could be due to the lower (albeit negative) correlation in recent years between GDP growth and oil prices due to asymmetric shocks (for instance, GDP growth was adversely affected by the November 2016 demonetization shock whereas oil prices were not). Further, the Fed Funds rate hikes over recent years could have affected capital flows and economic activity in emerging markets including India. For instance, in mid-2013, Federal Reserve’s signal about the possibility of tapering its security purchase had a negative impact on the financial conditions in several emerging markets, including India. Similarly, the Fed Funds rate hike in Q4 2015 was followed by a sharp drop in portfolio flows to India in Q1 2016. The normal-Wishart tight prior again dominates and is used in 36 of the top 50 forecasting models. The detailed forecast evaluation statistics for all 50 BVAR models are found in Table A.3 in the Appendix.

**Table 7: Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2011–Q1 2017 estimation period)**

Real	Monetary	Exogenous	Priors
15 GF	29 CPI, M1, REP	27 FF	36 Norm Tight
10 FEF	12 CPI, REP	23 None	14 Minn Loose
9 KD	1 CPI, M1		
14 EC	3 WPI, REP		
2 Mon	3 WPI, M1		
	2 WPI, M1, REP		

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, WPI = wholesale price index.  
 Source: Authors’ calculations.

Table 8 displays the top 10 BVAR forecasting models with the corresponding forecast evaluation statistics. Figure 13a (zoomed in further in Figure 13b) shows that the out-of-sample forecasts generated by these models are somewhat further away from the data than the models estimated over the 2004–2017 period. This could be due to major structural changes including inflation targeting and demonetization in the shorter, more recent sample. We tried controlling for structural breaks in these models, but this did not increase predictive accuracy. Anticipation effects, especially in advance of the inflation targeting regime, could explain why. While we can learn much about the predictive nature of these data by looking at the changing dynamics of the forecasting models over time, the findings suggest that it might be better to estimate the models over a longer period in light of the structural changes over the past few years.

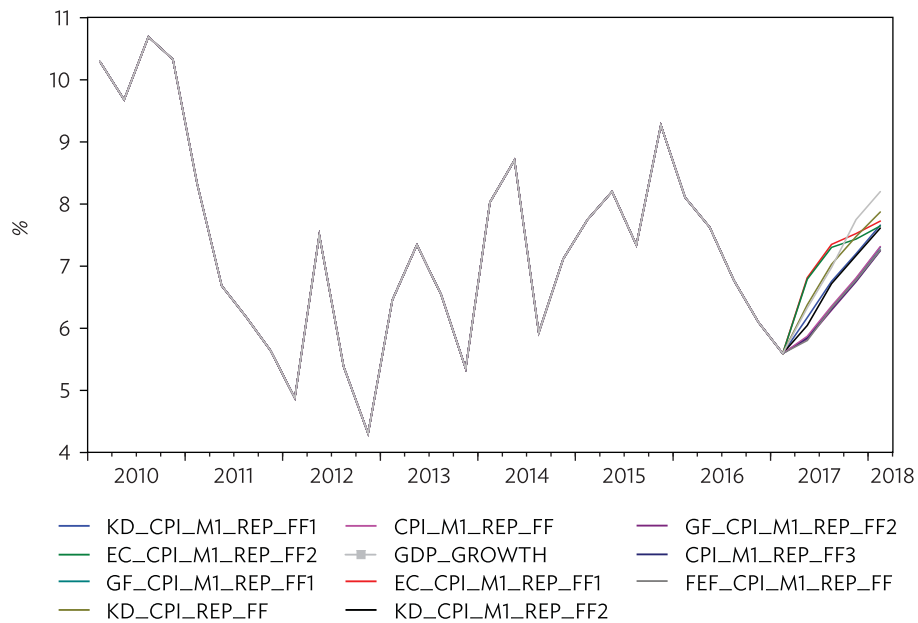
**Table 8: Top 10 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
1	KD3	CPI, M1, REP	FF	Norm Tight	0.028	0.028	0.016
2	EC4	CPI, M1, REP	FF	Norm Tight	0.046	0.035	0.024
3	EC3	CPI, M1, REP	FF	Norm Tight	0.047	0.035	0.024
4	KD1	CPI, M1, REP	FF	Norm Tight	0.049	0.039	0.025
5	GF2	CPI, M1, REP	FF	Norm Tight	0.051	0.040	0.026
6	GF3	CPI, M1, REP	FF	Norm Tight	0.051	0.041	0.026
7	KD3	CPI, REP	FF	Norm Tight	0.052	0.047	0.026
8	GF1	CPI, M1, REP	FF	Norm Tight	0.053	0.045	0.027
9	...	CPI, M1, REP	FF	Norm Tight	0.054	0.044	0.028
10	FEF1	CPI, M1, REP	FF	Norm Tight	0.055	0.044	0.028

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error.

Source: Authors' calculations.

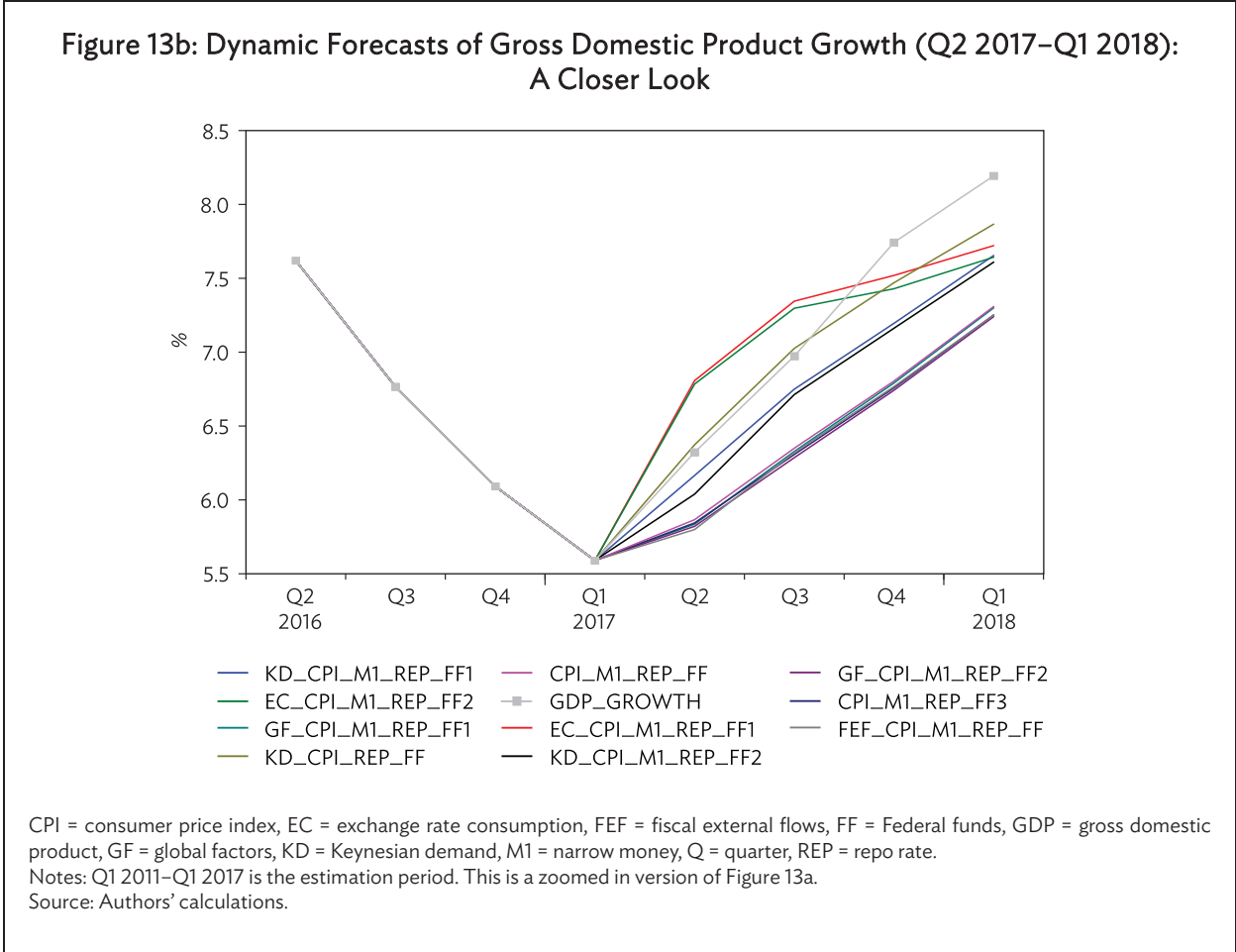
**Figure 13a: Dynamic Forecasts of Gross Domestic Product Growth (Q2 2017–Q1 2018)**



CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external factors, FF = Federal funds, GDP = gross domestic product, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate.

Note: Q1 2011–Q1 2017 is the estimation period.

Source: Authors' calculations.



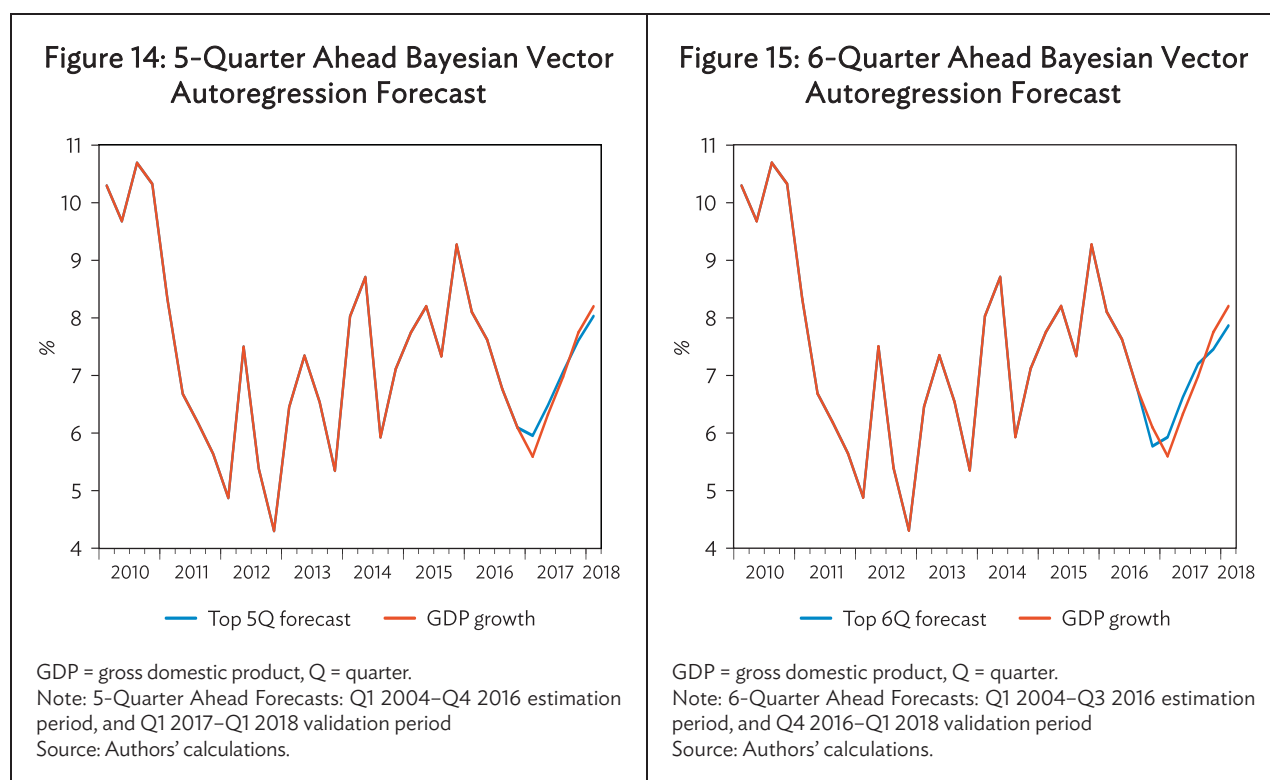
**D. Vector Autoregression and Structural Vector Autoregression Forecasts**

It is interesting to compare the predictive ability of the BVAR models with that of unrestricted VARs and more structured SVARs. VARs impose minimal assumptions on the data and are useful for forecasting purposes where identification is of secondary concern. A drawback of these models, however, is that of overparameterization. This results in multicollinearity, leading to inefficient estimates and potentially large forecast errors. We find that the BVAR forecasts generally outperform the VAR predictions. The relative forecast statistics of the top 10 BVAR models compared to their corresponding VARs for the two estimation samples are provided in Tables A.4 and A.5 in the Appendix.

SVARs are alternative forecasting models that impose economic theory to transform the hitherto unrestricted VAR into a system of structural equations. The SVARs are estimated using Choleski decomposition, a recursive identification scheme where the error terms in each regression equation is assumed to be uncorrelated with the error terms in the preceding equation. The identification schemes discussed in section III generally perform quite well, especially for the longer estimation sample starting in 2004, with three SVAR models in WPI inflation and two SVAR models in CPI inflation rivaling the forecasting accuracy of the BVAR models. The SVAR models are detailed in Table 3 in section III, and their corresponding forecast evaluation statistics are found in Tables A.6 and A.7 in the Appendix.

## E. Extending the Validation Period

The validation period for assessing the predictive ability of the specified models extends over the four latest quarters for which the macroeconomic data are available. While the four-quarter ahead dynamic forecasts provide quite a rigorous test of the out-of-sample forecast accuracy of the BVARs, we also vary the length of the validation period to five and six quarters. Given the nature of the macroeconomic data and economic policy in India, one potential concern with doing so is that in Q3 2016 there was a surprise demonetization that wiped out a significant amount of the currency from circulation and was thought to have widespread effects including a large short-term drag on economic activity. Due to the unexpected and highly impactful nature of the demonetization, beginning the validation period during and right after the shock in Q3 2016 and Q4 2016 could potentially lead to large forecast errors. We find, however, that the BVAR models are still able to predict GDP growth quite well, and the best five- and six-quarter ahead out-of-sample forecasts are provided in Figures 14 and 15 below.



## F. Inflation Forecasts

While it is not the primary purpose of this study to forecast inflation, we also assess the ability of the BVAR models in predicting CPI inflation, which is targeted by the RBI. The models are found to predict inflation dynamics well. A recent study across 14 EMEs (Duncan and Martinez-Garcia 2018) indicates that ARIMA models of inflation, especially a random walk, generally outperform more sophisticated models. The structural changes in the data, and often volatile indicators and inflation dynamics in EMEs can make inflation forecasting challenging. It seems, however, that the BVAR models of GDP growth in this study also have good predictive ability for inflation.



Table 9 provides the CPI inflation forecast evaluation statistics for the longer estimation sample beginning in Q1 2004, and Table A.8 in the Appendix does likewise for the estimation sample beginning in Q1 2011. We look at the inflation forecasts from the top 10 BVAR models as well as ARIMA models. Estimation of the ARIMA models for inflation proceeds in the same manner as the ARIMAs for GDP detailed earlier in this section. The best univariate model of inflation has 1 AR term and 4 MA terms for the estimation period beginning in Q1 2004, and 4 AR terms and 1 MA term for the estimation period beginning in Q1 2011. The top ARIMA models outperform a random walk model of inflation. Of particular note is that all the BVAR forecasts outperform the ARIMA models, which is an interesting finding from the standpoint of the literature and reiterates the relatively high informational content of quarterly BVAR models in India.

**Table 9: Dynamic Bayesian Vector Autoregression and Autoregressive Integrated Moving Average Forecasts of Consumer Price Index Inflation (Q1 2004–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
1	GF2	CPI, REP	OILS	Norm Tight	0.103	0.081	0.052
2	FEF2	CPI, REP	OILS	Norm Tight	0.104	0.083	0.052
3	KD4	CPI, REP	OILS	Norm Tight	0.104	0.083	0.053
4	...	CPI, REP	OILS	Norm Tight	0.105	0.085	0.053
5	KD4	CPI, REP	...	Minn Loose	0.112	0.086	0.057
6	FEF3	CPI, REP	OILS	Norm Tight	0.115	0.089	0.059
7	GF3	CPI, REP	OILS	Norm Tight	0.115	0.089	0.059
8	KD3	CPI, REP	OILS	Norm Tight	0.117	0.091	0.060
9	GF1	CPI, REP	OILS	Norm Tight	0.137	0.124	0.065
10	FEF1	CPI, REP	OILS	Norm Tight	0.229	0.194	0.104
11	Best ARIMA forecast for inflation (1 AR and 4 MA terms)				0.336	0.305	0.200

AR = autoregression, ARIMA = Autoregressive Integrated Moving Average, CPI = consumer price index, FEF = fiscal external flows, GF = global factors, KD = Keynesian demand, MA = moving average, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error.

Source: Authors' calculations.

## G. The Changing Dynamics of Gross Domestic Product Growth

The results from the empirical analysis so far suggest that FDI and portfolio flows are among the more significant variables relevant for predicting recent GDP growth in India. This finding is robust to changes in the estimation period and to revisions in the national accounts data, and holds true even after accounting for major shocks and structural changes in the sample including the GFC, demonetization, and shift toward an inflation targeting regime. It is a matter of interest, however, to assess whether the dynamics and predictability of GDP growth have changed over time. We therefore also predict GDP growth in the early 2000s, by setting the estimation period from Q1 2000 to Q4 2006, and the validation period four quarters ahead from that. This forecasting period is right before the GFC and around the time that exports in India started to grow rapidly due to the opening up of the economy.

A key finding is that trade linkages have high predictive power for GDP growth in the historical data. Thirty-five of the top 50 models, as found in Tables 10 and A9, include the 36-currency nominal



or real trade-weighted effective exchange rates. These models are based on the EC theory discussed in section III, where exchange rate fluctuations impact GDP growth through trade linkages and by affecting consumption patterns in developing countries that depend on traded goods (e.g., Iyer 2016, Cravino and Levchenko 2017). The high predictive power of the EC model is corroborated by the early 2000s data, which indicates that exports grew at a startling pace over the historical estimation sample, almost doubling as a fraction of GDP from 12% in Q1 2000 to over 22% in Q4 2006. Since then, however, export growth has slowed down, and exports as a fraction of GDP have been under 20% over the past few years. The slowdown in trade growth since the mid-2000s corresponds to the primary time period for most of the analysis in this paper and we find that the GF theory works well.

The findings also indicate that CPI inflation is a more relevant predictor for GDP growth than WPI inflation in the early 2000s. One reason why this might be the case is because the wealth effect created through the dramatic surge in export income could have eased liquidity constraints. The majority of households in India operate on a disposable income basis, as they do not have the financial means to borrow and save. Unlike the effects of a positive wealth shock in developed economies where most households are able to smooth consumption by hedging against shocks through assets, the positive wealth shock created by the surge in exports could have led to a significant increase in consumer spending pushing up CPI inflation (for more details on inflation in the 2000s in India, see Bhattacharya, Rao, and Sen Gupta 2014). Table 10 summarizes the results of the top 50 BVAR forecasting models, with the corresponding detailed forecast evaluation statistics found in Table A.9 in the Appendix.

**Table 10: Composition of the Top 50 Gross Domestic Product Growth Forecasts (Q1 2000–Q4 2006 estimation period)**

Real	Monetary	Exogenous	Priors
35 EC	6 CPI, REP	17 OIL	18 Norm Tight
8 KD	29 CPI, M1	11 FF	23 Norm Loose
4 GF	7 CPI, M1, REP	22 NONE	9 Minn Loose
3 Mon	4 WPI, M1, REP		
	4 WPI, REP		

CPI = consumer price index, EC = exchange rate consumption, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, WPI = wholesale price index.

Source: Authors' calculations.

## VI. CONCLUSION

This study seeks to forecast GDP growth in India using a BVAR framework. We also specify other time series econometric models such as VARs, SVARs, and ARIMAs. The models are used to forecast growth over the four most recent quarters as well as growth earlier in the 2000s. The BVAR models are based on macroeconomic specifications of the real and monetary sides of the Indian economy. We take into account the potential role of global factors in influencing growth in India as well as conventional aggregate demand variables, and control for exogenous variables such as oil prices. Given the changing nature of monetary policy over time in India, the models further assess alternative monetary theories that explain the underlying inflationary process in terms of the WPI versus the CPI.

The study estimates over 3000 BVAR models over two main periods that extend until Q1 2017, one longer and tracking back until 2004 and the second one more recent and starting in 2011. Dynamic forecasts of GDP growth are cast four quarters ahead, and the predictive ability of different models is compared based on a set of forecast evaluation statistics. We find that the best-performing BVAR models are able to almost perfectly capture the dynamics of Indian growth, especially over the longer estimation sample. These models also have good predictive capability for CPI inflation. The economic theory underlying the BVARs suggests that models that specify the inflationary process in terms of the CPI, as well as models that include FDI and portfolio flows, have high predictive content for recent GDP growth. BVAR models that capture trade linkages perform well in the early 2000s. The results from this study provide suggestive evidence that quarterly BVAR models of Indian growth have high predictive ability.

## APPENDIX

### Table A.1: Data Sources

Indicators	Source
Gross domestic product (GDP) at market price	Ministry of Statistics and Programme Implementation (MOSPI), Government of India
In 2004–2005 prices: Quarterly data from the first quarter (Q1) 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Government final consumption expenditure	MOSPI, Government of India
In 2004–2005 prices: Quarterly data from Q1 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Private final government expenditure	MOSPI, Government of India
In 2004–2005 prices: Quarterly data from Q1 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Gross fixed capital formation	MOSPI, Government of India
In 2004–2005 prices: Quarterly data from Q1 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Exports of goods and services	MOSPI, Government of India
In 2004–2005 prices: Quarterly data from Q1 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Imports of goods and services	MOSPI, Government of India
In 2004–2005 prices: Quarterly data from Q1 2005–2006 to Q3 2010–2011	
In 2011–2012 prices: Quarterly data from Q4 2010–2011 to Q1 2018–2019	
Trade balance	Directorate General of Commercial Intelligence and Statistics
Trade balance as a percent of GDP	Reserve Bank of India (RBI); Quarterly Estimates of GDP, MOSPI
Current account as a percent of GDP	RBI; Quarterly Estimates of GDP, MOSPI
Foreign direct investment as a Percent of GDP	RBI; Quarterly Estimates of GDP, MOSPI

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Table A.1 *continued*

Indicators	Source
Foreign portfolio investment as a percent of GDP	RBI; Quarterly Estimates of GDP, MOSPI
Consumer price index: Industrial workers: (General index): 2001=100	RBI: Handbook of Statistics on Indian Economy, Table 166
Consumer price index (Combined): 2012=100	RBI: Database on Indian Economy
Wholesale price index: 2011–2012=100	RBI: Database on Indian Economy
Index of industrial production: 2011–2012=100	RBI: Database on Indian Economy
Narrow money (M1)	RBI: Handbook of Statistics on Indian Economy, Components of Money Supply, Table 168
Broad money (M3)	RBI: Handbook of Statistics on Indian Economy, Components of Money Supply, Table 168
Repo	RBI: Weekly Statistical Supplement, Table 5
Reverse repo	RBI: Weekly Statistical Supplement, Table 5
Nominal effective exchange rate	RBI: Handbook of Statistics on Indian Economy, External Sector, Table 204
Real effective exchange rate	RBI: Handbook of Statistics on Indian Economy, External Sector, Table 204
Spot crude oil prices	Federal Reserve Economic Database (FRED), Federal Reserve Bank of St. Louis
Federal funds rate	FRED, Federal Reserve Bank of St. Louis

Source: Authors' compilation.

**Table A.2: Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
1	GF2	CPI, REP	OILS	Norm Tight	0.011	0.008	0.005
2	FEF2	CPI, REP	OILS	Norm Tight	0.011	0.009	0.006
3	KD4	CPI, REP	OILS	Norm Tight	0.011	0.011	0.006
4	...	CPI, REP	OILS	Norm Tight	0.012	0.008	0.006
5	KD4	CPI, REP	...	Minn Loose	0.013	0.011	0.006
6	FEF3	CPI, REP	OILS	Norm Tight	0.013	0.008	0.006
7	EC3	WPI, M1	...	Norm Loose	0.013	0.011	0.007
8	FEF1	WPI, REP	OILS, FF	Minn Loose	0.013	0.011	0.007
9	GF3	CPI, REP	OILS	Norm Tight	0.014	0.010	0.007
10	EC1	WPI, M1, REP	OILS, FF	Norm Loose	0.014	0.013	0.007
11	GF3	WPI, M1	OILS	Norm Tight	0.014	0.012	0.007
12	GF2	WPI, M1, REP	OILS	Norm Tight	0.014	0.013	0.007
13	GF2	WPI, M1	OILS	Norm Tight	0.014	0.013	0.007
14	GF3	WPI, M1, REP	OILS	Norm Tight	0.014	0.012	0.007
15	...	WPI, M1, REP	OILS	Norm Tight	0.014	0.012	0.007
16	KD3	CPI, REP	OILS	Norm Tight	0.014	0.011	0.007
17	GF1	CPI, REP	OILS	Norm Tight	0.015	0.010	0.007
18	...	WPI, M1	OILS	Norm Tight	0.015	0.012	0.007
19	FEF1	CPI, REP	OILS	Norm Tight	0.015	0.010	0.008
20	EC1	WPI, M1	...	Norm Loose	0.015	0.014	0.008
21	GF1	WPI, REP	OILS, FF	Norm Loose	0.015	0.012	0.008
22	GF1	WPI, REP	FF	Minn Loose	0.015	0.013	0.008
23	GF1	WPI, M1, REP	OILS	Norm Tight	0.015	0.013	0.008
24	KD2	CPI, REP	...	Minn Loose	0.015	0.011	0.008
25	FEF1	WPI, REP	OILS, FF	Norm Loose	0.015	0.012	0.008
26	GF1	WPI, M1	OILS	Norm Tight	0.016	0.013	0.008
27	KD1	CPI, REP	OILS	Norm Tight	0.016	0.012	0.008
28	EC3	WPI, M1, REP	OILS, FF	Norm Loose	0.016	0.013	0.008
29	GF3	WPI, M1	OILS, FF	Minn Loose	0.017	0.015	0.009
30	FEF3	WPI, REP	FF	Norm Loose	0.017	0.015	0.009
31	KD3	CPI, M1, REP	OILS	Norm Tight	0.017	0.014	0.009
32	GF1	WPI, M1	OILS + FF	Minn Loose	0.018	0.014	0.009
33	FEF1	WPI, M1, REP	OILS	Norm Tight	0.018	0.016	0.009
34	FEF3	WPI, M1, REP	OILS	Norm Tight	0.018	0.017	0.009
35	...	WPI, REP	FF	Minn Loose	0.018	0.017	0.009

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Table A.2 *continued*

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
36	KD3	CPI, REP	...	Minn Loose	0.018	0.017	0.009
37	EC3	WPI, M1, REP	...	Norm Loose	0.018	0.015	0.009
38	EC1	WPI, M1, REP	...	Norm Loose	0.018	0.017	0.009
39	GF3	WPI, REP	FF	Minn Loose	0.018	0.017	0.009
40	FEF3	WPI, M1	OILS	Norm Tight	0.019	0.018	0.009
41	GF1	CPI, M1, REP	OILS	Minn Loose	0.019	0.016	0.009
42	FEF2	WPI, M1, REP	OILS	Norm Tight	0.019	0.018	0.009
43	KD1	CPI, REP	...	Minn Loose	0.019	0.018	0.010
44	FEF2	WPI, M1	OILS	Norm Tight	0.019	0.018	0.010
45	FEF1	WPI, M1	OILS	Norm Tight	0.019	0.017	0.010
46	KD4	CPI, M1, REP	OILS, FF	Norm Tight	0.020	0.018	0.010
47	...	WPI, REP	OILS, FF	Norm Loose	0.020	0.016	0.010
48	GF3	WPI, REP	OILS, FF	Norm Loose	0.020	0.016	0.010
49	KD3	CPI, M1, REP	OILS, FF	Norm Tight	0.020	0.018	0.010
50	...	WPI, M1, REP	OILS, FF	Norm Tight	0.021	0.015	0.010

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error, WPI = wholesale price index.

Source: Authors' calculations.

**Table A.3: Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
1	KD3	CPI, M1, REP	FF	Norm Tight	0.028	0.028	0.016
2	EC4	CPI, M1, REP	FF	Norm Tight	0.046	0.035	0.024
3	EC3	CPI, M1, REP	FF	Norm Tight	0.047	0.035	0.024
4	KD1	CPI, M1, REP	FF	Norm Tight	0.049	0.039	0.025
5	GF2	CPI, M1, REP	FF	Norm Tight	0.051	0.040	0.026
6	GF3	CPI, M1, REP	FF	Norm Tight	0.051	0.041	0.026
7	KD3	CPI, REP	FF	Norm Tight	0.052	0.047	0.026
8	GF1	CPI, M1, REP	FF	Norm Tight	0.053	0.045	0.027
9	...	CPI, M1, REP	FF	Norm Tight	0.054	0.044	0.028
10	FEF1	CPI, M1, REP	FF	Norm Tight	0.055	0.044	0.028
11	KD3	CPI, M1, REP	...	Norm Tight	0.055	0.049	0.028
12	EC1	WPI, REP	...	Minn Loose	0.055	0.041	0.028
13	FEF2	CPI, M1, REP	FF	Norm Tight	0.056	0.043	0.028
14	EC1	WPI, M1	...	Minn Loose	0.056	0.042	0.029
15	EC3	WPI, REP	...	Minn Loose	0.058	0.042	0.030
16	FEF2	CPI, M1, REP	FF	Minn Loose	0.058	0.054	0.029

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Table A.3 *continued*

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
17	KD3	CPI, M1	FF	Norm Tight	0.058	0.046	0.030
18	EC1	WPI, M1, REP	...	Minn Loose	0.059	0.043	0.030
19	EC3	WPI, M1	...	Minn Loose	0.059	0.042	0.030
20	KD1	CPI, M1, REP	FF	Minn Loose	0.059	0.051	0.029
21	FEF3	CPI, M1, REP	FF	Norm Tight	0.059	0.044	0.030
22	GF3	CPI, M1, REP	FF	Minn Loose	0.059	0.053	0.029
23	KD3	CPI, REP	...	Norm Tight	0.059	0.054	0.030
24	FEF1	CPI, REP	...	Norm Tight	0.059	0.054	0.030
25	GF2	CPI, M1, REP	...	Norm Tight	0.060	0.048	0.030
26	FEF3	CPI, REP	...	Norm Tight	0.060	0.053	0.030
27	GF3	CPI, REP	...	Norm Tight	0.060	0.055	0.031
28	FEF1	CPI, M1, REP	...	Norm Tight	0.061	0.053	0.031
29	GF1	CPI, M1, REP	...	Norm Tight	0.061	0.055	0.031
30	EC3	CPI, M1, REP	...	Norm Tight	0.061	0.052	0.031
31	GF3	CPI, M1, REP	...	Norm Tight	0.061	0.051	0.031
32	FEF2	CPI, M1, REP	...	Norm Tight	0.061	0.046	0.031
33	GF1	CPI, REP	...	Norm Tight	0.061	0.056	0.031
34	FEF3	CPI, M1, REP	FF	Minn Loose	0.061	0.057	0.030
35	EC4	CPI, M1, REP	...	Norm Tight	0.061	0.053	0.031
36	KD1	CPI, M1, REP	...	Norm Tight	0.062	0.048	0.031
37	CE3	WPI, REP	...	Norm Tight	0.062	0.057	0.032
38	CE3	WPI, M1, REP	...	Minn Loose	0.062	0.044	0.032
39	GF2	CPI, M1, REP	FF	Minn Loose	0.062	0.054	0.031
40	EC4	CPI, M1, REP	FF	Minn Loose	0.063	0.054	0.031
41	EC3	CPI, M1, REP	FF	Minn Loose	0.063	0.054	0.031
42	...	CPI, M1, REP	...	Norm Tight	0.063	0.055	0.032
43	EC3	WPI, M1	...	Norm Tight	0.063	0.059	0.033
44	GF3	CPI, REP	FF	Norm Tight	0.063	0.057	0.032
45	FEF1	CPI, REP	FF	Norm Tight	0.063	0.058	0.032
46	KD3	CPI, M1, REP	FF	Minn Loose	0.063	0.054	0.031
47	GF3	CPI, REP	FF	Norm Tight	0.063	0.057	0.032
48	GF2	CPI, REP	FF	Norm Tight	0.064	0.055	0.033
49	GF1	CPI, REP	FF	Norm Tight	0.064	0.060	0.032
50	GF3	CPI, REP	FF	Norm Tight	0.065	0.047	0.033

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error, WPI = wholesale price index.

Source: Authors' calculations.

**Table A.4: Top 10 Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	RRMSFE (RW)	RRMSFE (VAR)
1	GF2	CPI, REP	OILS	0.011	0.782
2	FEF2	CPI, REP	OILS	0.011	0.791
3	KD4	CPI, REP	OILS	0.011	0.517
4	...	CPI, REP	OILS	0.012	1.015
5	KD4	CPI, REP	...	0.013	0.820
6	FEF3	CPI, REP	OILS	0.013	1.062
7	EC3	WPI, M1	...	0.013	0.220
8	FEF1	WPI, REP	OILS, FF	0.013	0.467
9	GF3	CPI, REP	OILS	0.014	1.021
10	EC1	WPI, M1, REP	OILS, FF	0.014	0.206

CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RRMSFE = relative root mean squared forecast error, RW = random walk, VAR = vector autoregression, WPI = wholesale price index.

Note: The root mean squared forecast error of each Bayesian vector autoregression is provided relative to the root mean squared forecast error of its corresponding vector autoregression in the last column.

Source: Authors' calculations.

**Table A.5: Top 10 Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	RRMSFE (RW)	RRMSFE (VAR)
1	KD3	CPI, M1, REP	FF	0.554	0.032
2	EC4	CPI, M1, REP	FF	0.951	0.046
3	EC3	CPI, M1, REP	FF	1.017	0.047
4	KD1	CPI, M1, REP	FF	1.083	0.049
5	GF2	CPI, M1, REP	FF	1.029	0.051
6	GF3	CPI, M1, REP	FF	1.052	0.051
7	KD3	CPI, REP	FF	0.713	0.052
8	GF1	CPI, M1, REP	FF	0.911	0.053
9	...	CPI, M1, REP	FF	0.921	0.054
10	FEF1	CPI, M1, REP	FF	0.994	0.055

BVAR = Bayesian vector autoregression, CPI = consumer price index, EC = exchange rate consumption, FEF = fiscal external flows, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RRMSFE = relative root mean squared forecast error, RW = random walk, VAR = vector autoregression.

Note: The root mean squared forecast error of each Bayesian vector autoregression is provided relative to the root mean squared forecast error of its corresponding vector autoregression in the last column.

Source: Authors' calculations.



**Table A.6: Structural Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2004–Q1 2017 estimation period)**

Recursive Identification Scheme	RRMFSE	RMAFE	Theil U
WPI, GDP, M1, REP	0.012	0.011	0.156471
WPI, GDP, M1, REP, [Ex: FF]	0.015	0.011	0.200434
CPI, GDP, M1, REP	0.017	0.012	0.222417
CPI, GDP, M1, REP, [Ex: FF]	0.019	0.016	0.252242
WPI, GDP, REP	0.020	0.017	0.240134
CPI, GDP, REP	0.026	0.024	0.318946
CPI, GDP, M1, REP, [Ex: OIL, FF]	0.032	0.030	0.309989
CPI, GDP, M1, REP, [Ex: OIL]	0.035	0.030	0.416284
CPI, GDP, REP, [Ex: FF]	0.047	0.042	0.581248
WPI, GDP, REP, [Ex: FF]	0.053	0.050	0.617851
WPI, GDP, M1, REP, [Ex: OIL, FF]	0.056	0.055	0.676907
WPI, GDP, M1, REP, [Ex: OIL]	0.067	0.063	0.767888
CPI, GDP, REP, [Ex: OIL]	0.071	0.070	0.839579
WPI, GDP, REP, [Ex: OIL]	0.092	0.091	1.103821
CPI, GDP, REP, [Ex: OIL, FF]	0.092	0.090	1.123632
WPI, GDP, REP, [Ex: OIL, FF]	0.096	0.096	1.137237

CPI = consumer price index, FF = Federal funds, GDP = gross domestic product, M1 = narrow money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error, WPI = wholesale price index.

Note: Structural vector autoregression identification scheme details are discussed in section III and summarized in Table 3. Source: Authors' calculations.

**Table A.7: Structural Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2011–Q1 2017 estimation period)**

Identification Scheme	RRMFSE	RMAFE	Theil U
WPI, GDP, M1, REP	0.059	0.049	0.029
WPI, GDP, M1, REP, [Ex: FF]	0.074	0.065	0.037
CPI, GDP, M1, REP	0.075	0.066	0.037
CPI, GDP, M1, REP, [Ex: FF]	0.078	0.069	0.039
WPI, GDP, REP	0.093	0.081	0.047
CPI, GDP, REP	0.107	0.091	0.055
CPI, GDP, M1, REP, [Ex: OIL, FF]	0.110	0.092	0.056
CPI, GDP, M1, REP, [Ex: OIL]	0.110	0.090	0.057
CPI, GDP, REP, [Ex: FF]	0.122	0.097	0.063
WPI, GDP, REP, [Ex: FF]	0.124	0.099	0.064
WPI, GDP, M1, REP, [Ex: OIL, FF]	0.137	0.119	0.072
WPI, GDP, M1, REP, [Ex: OIL]	0.154	0.129	0.082
CPI, GDP, REP, [Ex: OIL]	0.156	0.131	0.082
WPI, GDP, REP, [Ex: OIL]	0.156	0.128	0.083
CPI, GDP, REP, [Ex: OIL, FF]	0.171	0.147	0.090
WPI, GDP, REP, [Ex: OIL, FF]	0.176	0.152	0.094

CPI = consumer price index, FF = Federal funds, GDP = gross domestic product, M1 = narrow money, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error, WPI = wholesale price index.

Note: Structural vector autoregression identification scheme details are discussed in section III and summarized in Table 3. Source: Authors' calculations.

**Table A.8: Dynamic Bayesian Vector Autoregression and Autoregressive Integrated Moving Average Forecasts of Consumer Price Index Inflation (Q1 2011–Q1 2017 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMAFE	Theil U
1	KD3	CPI, M1, REP	FF	Norm Tight	0.515	0.455	0.052
2	EC4	CPI, M1, REP	FF	Norm Tight	0.532	0.469	0.052
3	EC3	CPI, M1, REP	FF	Norm Tight	0.537	0.486	0.053
4	KD1	CPI, M1, REP	FF	Norm Tight	0.544	0.504	0.053
5	GF2	CPI, M1, REP	FF	Norm Tight	0.556	0.494	0.057
6	GF3	CPI, M1, REP	FF	Norm Tight	0.559	0.516	0.059
7	KD3	CPI, REP	FF	Norm Tight	0.584	0.531	0.059
8	GF1	CPI, M1, REP	FF	Norm Tight	0.589	0.524	0.060
9	...	CPI, M1, REP	FF	Norm Tight	0.591	0.537	0.065
10	FEF1	CPI, M1, REP	FF	Norm Tight	0.608	0.541	0.104
11	Best ARIMA forecast of inflation (4 AR and 1 MA terms)				0.910	0.865	0.200

AR = autoregression, ARIMA = autoregressive integrated moving average, CPI = consumer price index, FF = Federal funds, M1 = narrow money, MA = moving average, Q = quarter, REP = repo rate, RMAFE = root mean absolute forecast error, RRMSFE = relative root mean squared forecast error.

Source: Authors' calculations.

**Table A.9: Top 50 Bayesian Vector Autoregression Forecasting Models of Gross Domestic Product Growth (Q1 2000–Q4 2006 estimation period)**

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMSFE	Theil U
1	EC2	CPI, M1	OILS	Minn Loose	0.071	0.068	0.035
2	EC2	CPI, M1, REP	OILS	Norm Tight	0.072	0.066	0.036
3	EC3	WPI, M1, REP	FF	Norm Loose	0.073	0.067	0.037
4	EC4	CPI, M1	OILS	Norm Loose	0.073	0.067	0.036
5	EC4	CPI, M1	OILS	Norm Tight	0.074	0.066	0.037
6	EC2	CPI, M1	...	Minn Loose	0.075	0.070	0.038
7	EC4	WPI, M1, REP	FF	Norm Tight	0.075	0.065	0.038
8	EC4	CPI, M1, REP	OILS	Norm Loose	0.075	0.065	0.038
9	EC2	CPI, M1, REP	OILS	Norm Loose	0.076	0.074	0.038
10	EC4	CPI, M1	FF	Norm Loose	0.077	0.066	0.039
11	KD	CPI, M1	...	Norm Loose	0.078	0.072	0.039
12	EC1	CPI, M1	...	Norm Tight	0.079	0.077	0.040
13	EC1	CPI, M1	OILS	Norm Tight	0.079	0.078	0.039
14	EC1	CPI, M1	...	Norm Loose	0.079	0.078	0.039
15	...	CPI, REP	OILS	Norm Tight	0.079	0.077	0.040
16	...	CPI, M1	OILS	Norm Loose	0.079	0.074	0.040
17	EC2	CPI, M1	FF	Norm Loose	0.079	0.061	0.040

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Table A.9 *continued*

Rank	Real	Monetary	Exo	Prior	RRMSFE	RMSFE	Theil U
18	EC3	CPI, M1	OILS	Norm Loose	0.079	0.071	0.040
19	EC1	WPI, M1, REP	FF	Norm Tight	0.079	0.066	0.040
20	GF2	WPI, REP	OILS	Norm Loose	0.080	0.070	0.040
21	KD1	CPI, M1	...	Norm Loose	0.080	0.076	0.040
22	EC3	CPI, M1, REP	OILS	Norm Tight	0.080	0.068	0.040
23	GF2	WPI, REP	OILS	Norm Tight	0.080	0.072	0.040
24	EC1	CPI, M1	OILS	Norm Loose	0.080	0.080	0.040
25	KD1	CPI, M1	FF	Norm Loose	0.080	0.068	0.041
26	EC2	WPI, M1, REP	FF	Norm Tight	0.080	0.063	0.040
27	KD4	CPI, M1	...	Norm Loose	0.080	0.071	0.041
28	EC2	CPI, REP	OILS	Minn Loose	0.080	0.068	0.040
29	EC4	CPI, M1, REP	...	Minn Loose	0.081	0.079	0.041
30	EC4	CPI, M1	...	Norm Tight	0.081	0.075	0.040
31	EC3	CPI, M1	...	Norm Loose	0.081	0.080	0.041
32	EC4	CPI, REP	FF	Norm Loose	0.081	0.078	0.041
33	EC4	CPI, M1, REP	...	Norm Loose	0.081	0.079	0.040
34	EC4	CPI, M1	...	Minn Loose	0.081	0.069	0.041
35	EC4	CPI, M1	OILS	Minn Loose	0.081	0.069	0.042
36	EC4	CPI, M1	...	Norm Loose	0.082	0.076	0.040
37	KD2	CPI, M1	FF	Norm Loose	0.082	0.067	0.042
38	KD2	CPI, M1	...	Norm Tight	0.082	0.069	0.042
39	KD1	CPI, M1	...	Norm Tight	0.082	0.074	0.042
40	KD2	CPI, REP	...	Minn Loose	0.082	0.080	0.041
41	GF2	WPI, REP	...	Norm Loose	0.082	0.082	0.041
42	EC1	CPI, M1	OILS	Norm Tight	0.082	0.075	0.042
43	EC2	CPI, REP	FF	Norm Tight	0.082	0.074	0.042
44	EC2	CPI, M1, REP	...	Norm Loose	0.082	0.079	0.041
45	EC2	CPI, M1	...	Norm Tight	0.083	0.073	0.041
46	GF2	WPI, REP	...	Minn Loose	0.083	0.080	0.042
47	...	CPI, M1	...	Norm Loose	0.083	0.082	0.042
48	EC1	CPI, M1	...	Minn Loose	0.083	0.074	0.042
49	EC4	CPI, REP	FF	Norm Tight	0.083	0.083	0.042
50	EC3	CPI, M1	...	Norm Tight	0.083	0.078	0.042

CPI = consumer price index, EC = exchange rate consumption, FF = Federal funds, GF = global factors, KD = Keynesian demand, M1 = narrow money, Q = quarter, REP = repo rate, RMSFE = root mean squared forecast error, RRMSFE = relative root mean squared forecast error, WPI = wholesale price index.

Source: Authors' calculations.

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## **Quarterly Forecasting Model for India’s Economic Growth: Bayesian Vector Autoregression Approach**

This paper presents a framework for forecasting India’s gross domestic product (GDP) growth on a quarterly basis. The framework, based on Bayesian econometric methods, is found to have high predictive ability. Useful findings emerge on the particular variables that are responsible for explaining GDP growth in India. The best-performing models take into account the influence of capital flows in driving growth over the past decade and trade linkages in influencing growth in the early 2000s. Overall, the results from this study provide suggestive evidence that Bayesian vector autoregression methods are highly effective in predicting GDP growth in India.

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