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Nowcasting economic growth in India: The role of rainfall

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NOWCASTING ECONOMIC GROWTH IN INDIA

THE ROLE OF RAINFALL

Tara Iyer and Abhijit Sen Gupta

NO. 593

October 2019

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Nowcasting Economic Growth in India The Role of Rainfall

Tara Iyer and Abhijit Sen Gupta

No. 593 | October 2019

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ABSTRACT

This study provides a toolkit to nowcast, or produce early estimates of, gross domestic product (GDP) growth in India. We use a dynamic factor model (DFM) to nowcast GDP growth in India on a quarterly basis from January 2000 to December 2018. The DFM methodology offers a powerful and tractable means of nowcasting economic growth while accounting for mixed-frequency data, which is data released on different dates, and missing time series. The specified DFM, which includes six quarterly indicators and 12 higher-frequency monthly variables, is able to effectively nowcast growth in India. The variables in the framework are drawn from the real, monetary, financial, and external sectors in India and selected to represent aggregate economic activity. There are several interesting results in the study. A key finding is that rainfall has high predictive content for GDP growth in India, a novel result from the viewpoint of the existing nowcasting literature.

Keywords: dynamic factor model, GDP growth, India, nowcasting, rainfall

JEL codes: C32, C53, Q56

I. INTRODUCTION

Time series on key economic indicators are often released with substantial delays in advanced and developing economies alike. A closely tracked indicator is quarterly gross domestic product (GDP) growth, often considered a useful summary measure of the present state of the economy. In the United States, official estimates of growth are released around a month after the reference quarter. In the euro area, GDP growth estimates are available only after a lag of around 6–7 weeks. In Indonesia, a large emerging market economy in Asia, quarterly growth estimates are typically released with a lag of around 5 weeks. In India, one of the fastest-growing large emerging market economies in the world, official quarterly GDP growth figures are released approximately 2 months after the reference quarter.

The delays in the release of official economic statistics can pose difficulties to policy makers and financial market participants whose decision making depends intrinsically on the availability of timely and accurate data. Over the past decade, economists have tried to address this issue by developing a technique called nowcasting, which involves generating current estimates of key statistics that would otherwise only be published much later. Nowcasting models employ data that is available at higher frequencies than the variables of interest. The aim is to predict the present and very near future using expert judgment and quantitative methods. This study seeks to nowcast quarterly GDP growth in India by developing an econometric framework specific to the Indian economy.

We use a dynamic factor model (DFM) to predict GDP growth. DFMs have been used in the literature to nowcast economic growth in advanced as well as emerging market economies. The model we employ is based on the framework by Doz, Giannone, and Reichlin (2011, 2012) and Luciani et al. (2015). DFMs are based on a few components that each capture the comovement among multiple time series. A key advantage of DFMs is that they account for the nonsynchronicity of data releases and can easily deal with mixed-frequency indicators as well as data released on different dates. This allows for the inclusion of series that are released on different dates and more often than quarterly GDP growth. These models can also handle missing data, which is particularly useful in emerging market economies. DFMs have a good track record as they have been successfully used to generate nowcasts for other emerging market economies: the People's Republic of China (PRC) (Giannone et al. 2014); Brazil (Bragoli, Metelli, and Modugno 2014); and Indonesia (Luciani et al. 2015).

There are three main findings in this study. First, in developing a toolkit for nowcasting in India, we find that rainfall has high predictive content for GDP growth. This is the first such result that we know of in the nowcasting literature. At the first sight, the importance of rainfall is surprising given that agriculture and allied activities account for only 16% of overall output. However, the sector continues to support more than 47% of the workforce and hence, large deviations from normal rainfall adversely affect the earning potential of these workers, which in turn depresses private consumption. Rainfall remains vital to agricultural productivity due to the pervasive scarcity of water supply (World Bank 2018). Around 52% of overall cropped area in India remains without irrigation, with certain regions being chronically water stressed (Mishra 2017).

Second, the predictive content of rainfall for growth has declined slightly over time. While rainfall remains highly informative for GDP growth in earlier as well as more recent time periods, its diminishing influence could arise as India has been transitioning from an agrarian society toward a more urbanized nation over the past few decades.

Third, the structural and stabilization policies enacted by the government since the liberalization of the 1990s appear to have positively affected economic activity. We find that the

specified DFM framework significantly improves over a random walk (RW) model of GDP growth over a 2000–2018 estimation period. The average root mean squared error (RMSE), which is the mean of RMSEs computed recursively over a sequence of data samples, reduces by around 40% for the DFM nowcast relative to an RW. During an earlier estimation period of 2000–2008, however, the RW model has a 17% lower RMSE than the DFM. Along with the increased predictability of GDP growth, the declining informational content of variable monsoons for growth suggest that stabilization policies have been effective in increasing the resilience of the Indian economy to idiosyncratic shocks.

Other results in the study include that macrofinancial indicators in the DFM, such as credit extended by banks, the National Stock Exchange (NSE) index, and commercial bank investments, have high predictive content for growth. These variables are monthly and thus, of higher frequency than quarterly GDP growth, which is useful as the DFM updates its growth projections each time such a higher frequency indicator is released. A total of 18 variables from the real, monetary, financial, and external sectors specific to the Indian economy are included in the model. Other monthly variables include vehicle sales; monetary policy indicators, such as the repo rate and the cash reserve ratio; the consumer price index (CPI); money; the oil price index and imports of petroleum; rainfall; and the deviation of rainfall from its mean in any given month. The quarterly variables include a business confidence index and the components of GDP based on the expenditure approach, which we find have high predictive power.

The rest of the study proceeds as follows. Section II presents a brief review of the literature on nowcasting. Section III highlights some of the trends and issues with Indian GDP data. Section IV presents an endogenous growth model of agriculture and GDP growth to highlight the channels through which rainfall might affect economic activity. Section V describes the DFM that we use for the purposes of nowcasting GDP growth. Section VI discusses the data used in the study. Section VII provides the empirical results on the predictability of GDP growth. Section VIII concludes and offers some policy implications.

II. A BRIEF REVIEW OF THE LITERATURE

The literature on nowcasting, or producing early estimates of, GDP growth is fairly recent. Most academic papers use DFMs, originally proposed by Giannone, Reichlin, and Small (2008). DFMs employ a state space representation in a formal statistical framework, thereby advancing the methodology of nowcasting from the previously used combination of bridge equations (which are simple regressions of GDP growth on a few key monthly variables) and judgment. Giannone, Reichlin, and Small (2008) develop a state space model with measurement equations, which link the observed time series with latent state variables, and transition equations, which describe the dynamics of the state variables. The usage of a Kalman filter for the purposes of estimation makes it possible for DFMs to handle mixed-frequency data, missing data, and “jagged edge” datasets, which consist of time series released on different dates.

Over the past decade, DFMs have been used to nowcast GDP growth in advanced countries and regions including the United States (e.g., Lahiri and Mnokroussos 2011), France (Bessec and Doz 2011), Germany (Marcellino and Schumacher 2010), the euro area as a whole (e.g., Angelini et al. 2011), Norway (Aastveit and Trovik 2012), and New Zealand (e.g., Matheson 2010). For an excellent survey of the literature and details on these studies, see Banbura et al. (2013). DFMs have also been applied to individual emerging market economies more recently such as the PRC (Giannone et al. 2014); Brazil (Bragoli, Metelli, and Modugno 2014); Indonesia (Luciani et al. 2015); and for a group of emerging markets including Brazil, Indonesia, Mexico, South Africa, and Turkey (Cepni, Guney, and

Swanson 2018). For India in particular, notable nowcasting attempts exist by Bhattacharya, Pandey, and Veronese (2011) and Bhadury et al. (2018).

Bhattacharya, Pandey, and Veronese (2011) use a bridge model to nowcast GDP growth on a quarterly basis in India. The model meets with moderate success, and the authors find that survey data in India only incrementally improves the performance of the bridge regressions, in contrast to the higher predictive power that survey data has in advanced economies. Our study contributes by using the more rigorous DFM methodology and by nowcasting GDP growth in India until 2018. Bhadury, Beyer, and Pohit (2018) employ a DFM to forecast the growth of gross value added (GVA) in India. They use monthly indicators to track each of the components of GVA. The authors find that nightlight intensity has good informational content for GVA in India. This paper differs from Bhadury, Beyer, and Pohit (2018) by nowcasting GDP instead of GVA, and by employing a very different set of high-frequency indicators. Furthermore, a key result in this study that contributes to the existing nowcasting literature is that rainfall has high predictive content for economic growth in India.

III. TREND OF INDIAN GROSS DOMESTIC PRODUCT GROWTH

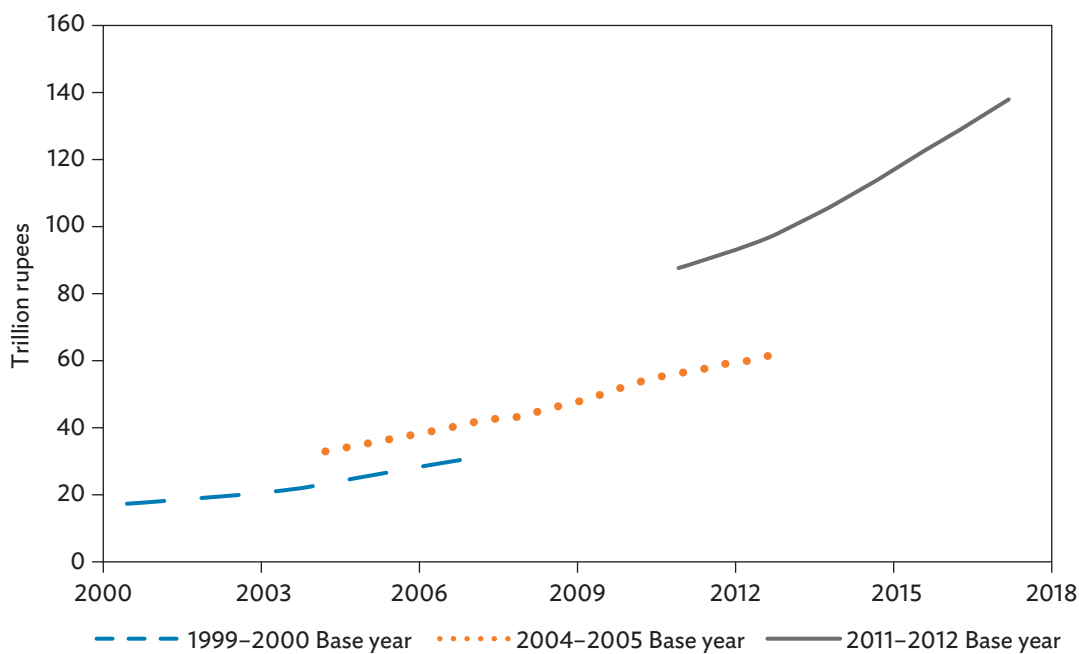
Data on GDP in India is prepared by the Central Statistics Office in the Ministry of Statistics and Program Implementation. Since 1996, India has been publishing quarterly GDP data with a lag of around 2 months.¹ The quarterly data is released on 31 August (April–June quarter), 30 November (July–September quarter), 28 February (October–December quarter), and 31 May (January–March quarter). However, the data is revised several times subsequently. At the time of the release of the third quarter estimates on 28 February, the quarterly estimates of the previous 2 years and the first and second quarter estimates of the current year are revised. Subsequently, on 31 May, when data on the fourth quarter of the previous fiscal year is released, the data for the first three quarters are also revised. These revisions continue over the next 3 years with the final data appearing 2 years and 10 months after completion of the fiscal year (CSO 2016)

As discussed in Sapre and Sengupta (2017), the revisions are driven by availability of additional and improved data. These include (i) availability of complete data on high frequency indicators, (ii) replacing indicators with direct data sources where available, and (iii) replacing data with indirect data sources including surveys.

Apart from revisions on account of availability of better-quality data, periodic revisions are made to the methodology of calculating GDP and to rebase the GDP to a new price level. This is a routine practice in various statistical offices to account for the structural changes taking place in the economy and in relative prices and to replace older survey data with newer surveys that more accurately capture economic activity (Nagraj 2017). Since 2000, India's GDP data is available across different base years i.e., 1999–2000, 2004–2005, and 2011–2012 with a few years of overlap across the series. These are plotted in Figure 1. However, the divergence in the slope across the series indicate that the revision in methodology has also resulted in different growth rates. A similar finding has been reported for Indonesia by Luciani et al. (2015)

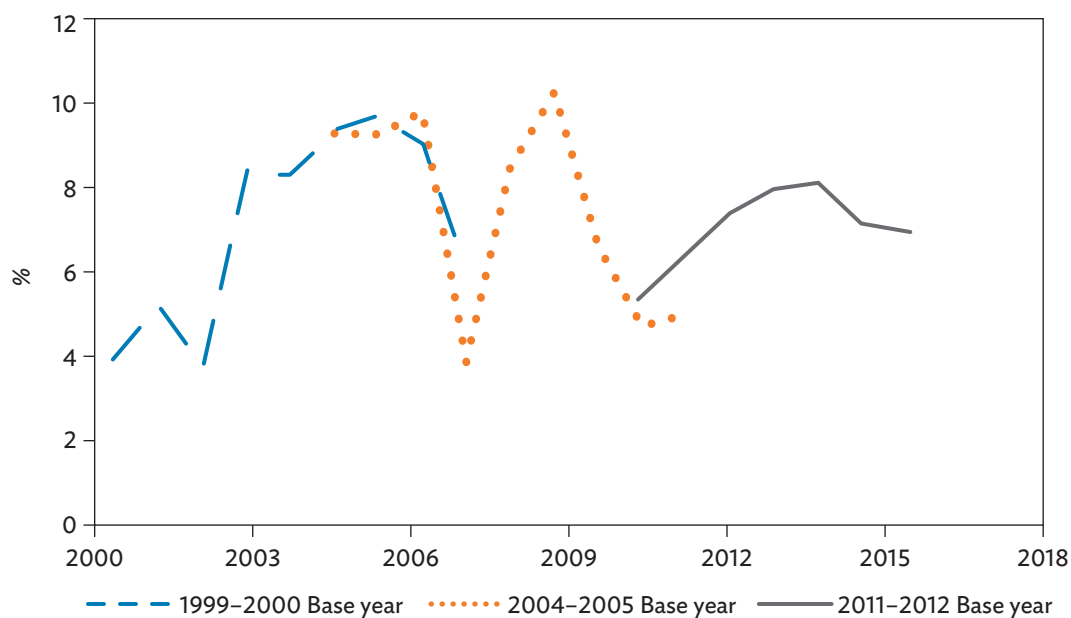
¹ The Indian fiscal year begins on 1 April and culminates on 31 March of the subsequent year.

Figure 1: Annual Real Gross Domestic Product



Source: Economic Outlook Database, Centre for Monitoring Indian Economy. <https://economicoutlook.cmie.com/> (accessed 25 April 2019).

Figure 2: Annual Real Gross Domestic Product Growth

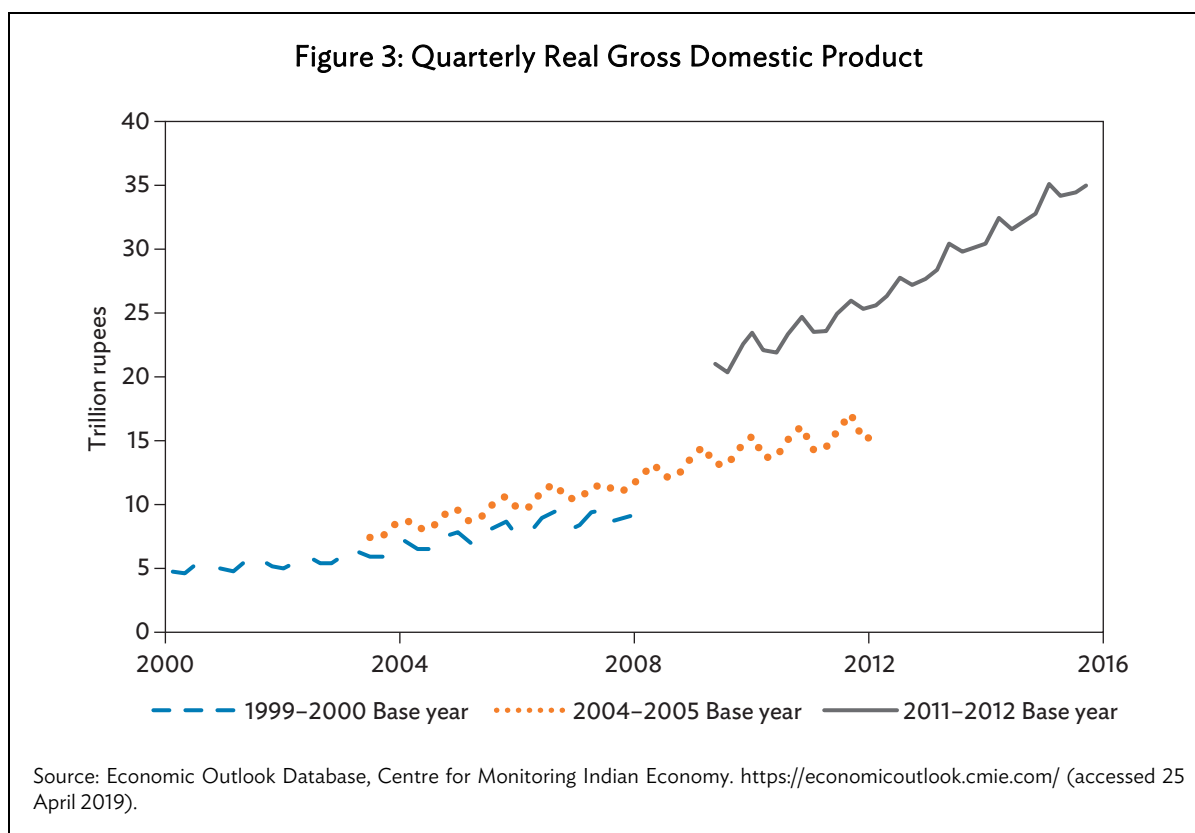


Source: Economic Outlook Database, Centre for Monitoring Indian Economy. <https://economicoutlook.cmie.com/> (accessed 25 April 2019).

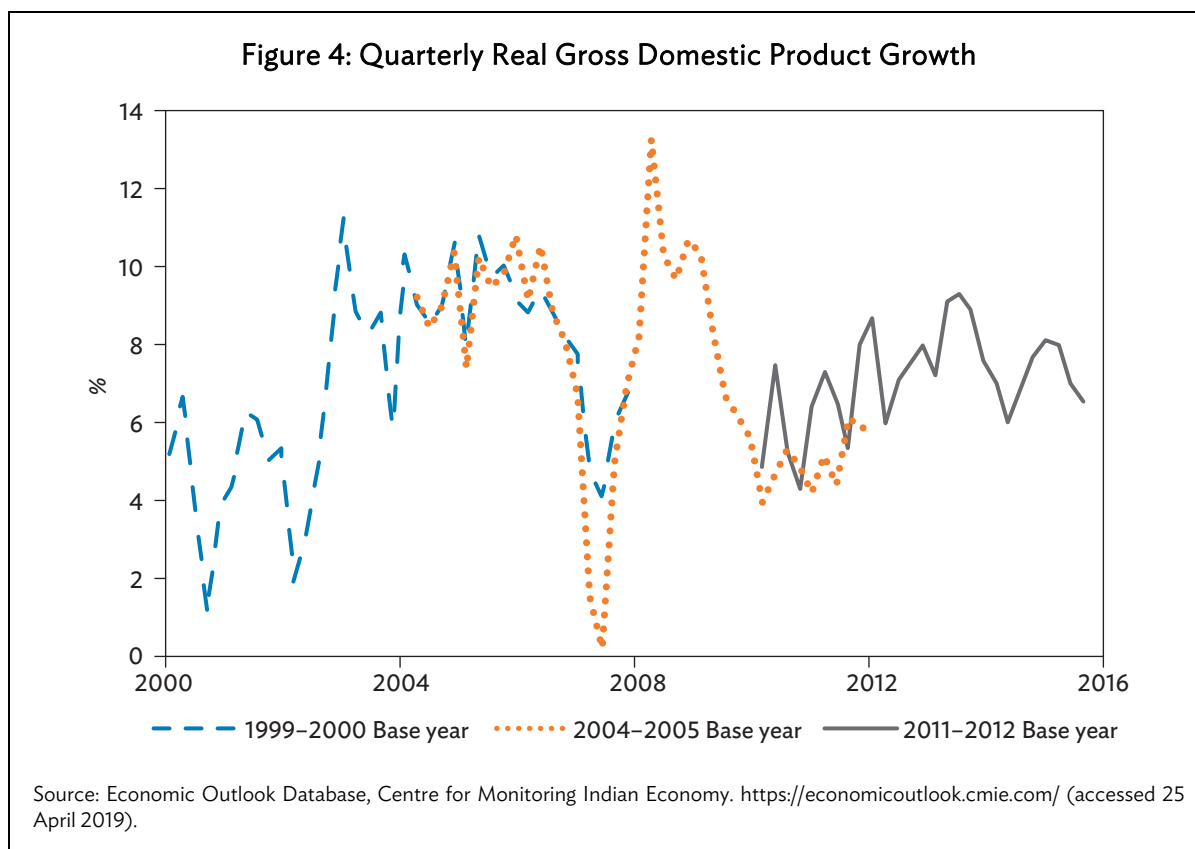
Figure 2 plots the annual year-on-year growth rate of real GDP. Growth steadily picked up from 3.8% in 2002 to average over 9% during 2005–2007 according to the 1999–2000 series. The high growth during 2005–2007 is also corroborated when GDP is calculated based on the 2004–2005 series. However, the 2004–2005 series records a much sharper dip in growth during the global financial crisis (GFC) in 2008, compared to the 1999–2000 series. India revived fairly quickly from the GFC recording an average growth of over 9% during 2009 and 2010. However, economic activity decelerated from 2011 onward slowing down to an average of 5.5% during 2011–2013 according to the 2004–2005 series. The 2011–2012 series showed a smaller dip in growth during 2012 and 2013 compared to the 2004–2005 series.² Growth steadily inched up to over 8% in 2016 but has witnessed a decline in recent years.

In Figures 3 and 4, we focus on the quarterly GDP series since 2000. As expected, the quarterly GDP series is more volatile compared to the annual series both in levels and in growth rate.

The quarterly GDP data also exhibits significant seasonality with economic activity in most fiscal years sequentially picking up during the course of the year, implying economic activity would be at its lowest level in the first quarter and would reach its peak in the fourth quarter. In some years, especially those covered by the 1999–2000 base year, the second quarter GDP numbers tend to be the lowest. As quarterly, not annual, national accounts statistics are used for the purposes of nowcasting, the seasonality in the quarterly time series is addressed by using year-on-year growth rates in the model.



² For a comprehensive analysis on the differences in GDP growth across 2004–2005 and 2011–2012 base year series please see Nagaraj and Srinivasan (2017).



IV. A MODEL OF RAINFALL AND GROSS DOMESTIC PRODUCT GROWTH

The Indian economy is uniquely reliant on rainfall. Rainfall is vital for the livelihood of much of India's 1.3 billion population as it plays a key role in determining the productivity of the agriculture sector. The agriculture sector employs around 47% of the workforce, occupies 60% of the country's land, and uses 90% of its water resources (World Bank 2018). Close to 55% of agricultural yields directly depend on rainfall due to factors such as poorly developed irrigation systems. Groundwater resources are also rapidly depleting due to demand from growing cities, farms, and factories as well as overpumping by farmers. India presently ranks among the world's most water-stressed countries. Water scarcity in India makes the agriculture sector highly susceptible to volatile monsoon events.

The relationship between rainfall, climate, and economic growth is examined by a vast literature (reviewed in Dell, Jones, and Olken 2014). Several studies focus on the correlation between rainfall and agriculture and the ensuing effects on economic activity. For instance, Barrios, Strobl, and Bertinelli (2010), in a study of the effects of rainfall and temperature variations on per capita GDP growth in a sample of sub-Saharan African economies between 1960 and 1990, document that rainfall is significantly positively correlated with growth. For India, Virmani (2006) and Gadgil and Gadgil (2006) analyze the relationship between rainfall and GDP growth from 1951 to the early 2000s. Both studies find that a 1% increase in rainfall relative to its mean is correlated with a 0.16% increase in GDP growth.

In a recent paper, Namoto (2016) analyzes the impact of rainfall on India's macroeconomic performance, distinguishing between the agriculture and nonagriculture sectors. The study estimates the impact of rainfall on economy activity from 1952 to 2013 using a generalized least squares

approach to estimate the average impact and the Kalman filter to estimate the time-varying impact. The results indicate that rainfall has a significant impact on aggregate economic activity, and this arises through its effects on the agriculture sector. Matsuyama (1992) and Irz and Roe (2005) develop endogenous growth models with a role for agriculture. In this section, we present the framework used in Irz and Roe (2005) to better understand the links between rainfall and economic growth.

Consider a developing economy comprised of two sectors: an agriculture sector and another nonagriculture sector that engages in other economic activities such as manufacturing. Each sector employs capital and labor and has a sector-specific technology. The agriculture sector, in contrast to manufacturing, also uses land as an input in its production function. The production functions of each sector are in the Cobb–Douglas form and can be written as

$$Y_a = R_a K_a^{\beta_1} L_a^{1-\beta_1} T^{1-\beta_2} \text{ and } Y_m = A_m K_m^\alpha L_m^{1-\alpha} \quad (1)$$

where the subscripts a and m stand for agriculture and manufacturing, respectively. In the production functions, Y_a and Y_m represent output; K_a , K_m , L_a , and L_m are the capital and labor services employed by each sector; and β_1 and α are the output elasticities of capital in the agriculture and manufacturing sectors, respectively. T represents the land required to cultivate agricultural produce and is a fixed commodity. A_m is an exogenous technology shock, while R_a is an exogenous rainfall shock.

Note that as agriculture depends on land, which is a fixed resource, the labor and capital employed in this sector face diminishing returns in contrast to the inputs in the manufacturing sector. Furthermore, we assume that the exogenous source of variation in the agriculture sector is captured by weather shocks, specifically on idiosyncratic precipitation and volatile monsoon events. While simplistic, this captures one of the primary sources of uncertainty in the Indian agriculture sector.

The representative household in the economy maximizes utility over an infinite horizon as follows

$$\text{Max}_{c_{at}, c_{mt}} \int_0^\infty u\left(\frac{c_{at}c_{mt}-1}{1-\theta}\right)^{1-\theta} e^{-\rho t} e^{nt} dt \quad (2)$$

where u is the instantaneous utility function, ρ is the discount rate, n is the rate of population growth, $1/\theta$ is the elasticity of intertemporal substitution, c_{at} and c_{mt} denote the per capita consumption of agriculture and manufactured goods at time t . Utility is maximized subject to a sequence of budget constraints. In each period, the flow budget constraint of the household is written as

$$\dot{k} = w + (r - n - \delta)k + s\tau - c_m - pc_a \quad (3)$$

The budget constraint formalizes that the household consumes agricultural produce and manufactured goods. The household derives its income from wages, w , the rental of capital services per capita, k , at rate r , and the rental of land services per capita, τ , at rate s . p is the relative price of agriculture in terms of manufactured goods. The equilibrium condition for p is given below. Note that the consumption of agricultural goods appears in the optimization problem of the household. This implies that the rainfall shock, which affects agricultural production, directly impacts consumption patterns and hence, aggregate economic activity.

An equilibrium for this economy exists when the representative consumer maximizes utility; the producers maximize profit; the markets clear for land, labor, and capital; and a no-arbitrage

condition holds between the two assets, capital and land. The six equilibrium conditions describe the short- and medium-term growth of real GDP in the economy. The equations describing the evolution of economic growth form a system of differential equations that can only be solved numerically. We provide the equation determining the relative price in the economy here, p , which depends on the rainfall shock, R_a . The rest of the equilibrium conditions can be found in Irz and Roe (2005).

$$p = \frac{r^{\beta_1} w^{\beta_2}}{R_a} \left(\frac{1-\beta_1-\beta_2}{\alpha\beta_2-\beta_1(1-\alpha)} \frac{\alpha w - rk(1-\alpha)}{\tau} \right)^{1-\beta_1-\beta_2} \quad (4)$$

The model has a few key implications. While it is outside the scope of this section to present the numerical simulations, which are derived using the shooting method solution to boundary value problems, the primary finding is that the equilibrium growth paths of all key variables in the economy depend on agricultural productivity and rainfall. Moreover, the rainfall shock affects the economy more in the short run. In the eventual steady state, when the state of economic development converges to that in a high-income economy, GDP growth is finally not affected by rainfall. This makes sense as greater economic development increases resilience to idiosyncratic shocks. The theoretical implications of this model of rainfall and growth are fully borne out by the empirical results in this study.

V. NOWCASTING FRAMEWORK

This paper uses a DFM to nowcast GDP growth in India. The underlying motivation behind nowcasting is to produce estimates of quarterly growth rates before the release of official national account statistics based on higher-frequency indicators. The nowcasting results can be interpreted as quarterly estimates of annual (year-to-year) GDP growth based on the most current and relevant mixed-frequency economic and financial data available. There are various advantages to using a DFM framework for nowcasting. To start with, it is possible to generate current GDP growth estimates based on an established quantitative econometric framework rather than potentially biased subjective judgments.

A DFM is also well suited to handle mixed-frequency data as well as data released on different dates. This allows for the inclusion of data series that have significant predictive power for GDP growth, but which are released on different dates and on a higher frequency basis than quarterly GDP growth. Furthermore, a DFM can be estimated on a large number of relevant variables, allowing the modeler to potentially adjust the dimensions of the model as structural change or shocks occur. DFMs can also handle missing data, which is particularly useful in developing countries. Finally, DFMs have a good track record as they have been successfully used to generate nowcasts for other emerging market economies: the PRC (Giannone et al. 2014); Brazil (Bragoli, Metelli, and Modugno 2014); and Indonesia (Luciani et al. 2015).

The DFM framework that we employ in this study is based on the econometric specifications in Doz, Giannone, and Reichlin (2011, 2012) and Luciani et al. (2015). A dynamic factor is a variable that captures the comovement among multiple data series. As such, each variable, x_{it} , in the DFM can be decomposed into two components: (i) y_t , which is a vector of common factors; and (ii) ε_{it} , which is an idiosyncratic term. At time period t , the i^{th} variable in the model, x_{it} , can be written as

$$x_{it} = \lambda_i y_t + \varepsilon_{it} \quad (5)$$

where $i = 1, \dots, n$. The i^{th} error term, ε_{it} , follows a first-order autoregressive (AR) process driven by white noise, e_{it} : $\varepsilon_{it} = \sigma_i \varepsilon_{it-1} + e_{it}$.

An unrestricted vector autoregression (VAR) structure is imposed on y_t , implying that the distribution of the parameter vector in the VAR, $\beta \equiv \text{vec}([\mu, \beta_1, \dots, \beta_k]')$, can be computed through ordinary least squares. The VAR is written as

$$y_t = \mu + \beta_1 y_{t-1} + \dots + \beta_k y_{t-k} + u_t \quad (6)$$

where the vector of error terms, u_t , is normally distributed with a mean set of zeros and covariance matrix Σ , $u_t \sim N(0, \Sigma)$.

The DFM is estimated using maximum likelihood. The model solution is computed using an expectation-maximization algorithm as in Luciani et al. (2015) and as originally proposed by Banbura and Modugno (2014). This algorithm is useful for nowcasting as it is able to account for missing data and time series that are of mixed frequencies. To assess the performance of the framework, we compare the DFM nowcasts with nowcasts using AR and RW models of growth. The predictive ability of the specified DFM will be discussed in section VII, which presents the empirical results.

VI. DATA

The data used in the nowcasting framework is of mixed frequency with monthly and quarterly indicators. The dataset extends from January 2000 to the third quarter of 2018. 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 to June, and the last quarter extends from January to March of the subsequent year. We draw the variables from several databases including the Ministry of Statistic and Program Implementation, the Reserve Bank of India (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 Appendix Table A1.

The time series 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 account for structural change. For further details on the 2011–2012 price series, please see NSC (2018). Since our dataset traces 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 Consumer Price Index (CPI), since these data are only available from the fourth quarter of 2010, we backcast the series using the reweighed CPI industrial workers.

We use a variety of economic and financial indicators. GDP is often calculated in countries through the expenditure approach. In terms of quarterly data, we collect time series on investment, government expenditure, private consumption, exports, and imports as per the expenditure approach. We also collect data on the major components of GVA—agriculture, industry, and services. The dataset includes external sector variables such as net foreign direct investment, net portfolio flows, the current account, and external debt. We additionally use quarterly time series on House Price and Business Expectations Indexes.

Besides the quarterly indicators, numerous economically significant monthly indicators are included in the dataset. This allows us to exploit information that is released earlier and is of higher frequency than GDP growth to estimate quarterly growth figures before the official estimates are available. Time series on the CPI, which the RBI currently targets, and the Wholesale Price Index, which the RBI used to previously focus on, are collected, as is data on the Index of Industrial

Production. We further collect monthly data on various measures of the monetary base to account for money, given the predominantly cash-based nature of economic activity in India. Series on the RBI's holdings of gold reserves as well as currency in circulation are also included.

We assess the importance of macrofinancial linkages by including key financial variables of monthly frequencies. An index of India's leading stock exchange, the NSE, is collected as are various indicators of credit extended by banks (total credit, food credit, nonfood credit, credit to agriculture, credit to industry, credit to services). We also include data on commercial bank investments. Next, data on total electronic fund transfers in India is collected to account for the increasing role of e-payments through the RBI's encouragement of alternative modes of payment via mobile devices and the internet. Time series on real time gross settlement transfers, which represent immediate interbank electronic transfers, as well as aggregate credit and debit card usage, are also included to account for the growing importance of electronic payment systems in India.

Monthly time series are collected on the 3-month and 10-year Treasury yields to assess the predictive significance of the yield curve. The dataset also includes monthly indicators on total exports and imports of goods and services, as well as data on exports and imports of key commodities such as petroleum, agriculture, chemicals, engineering goods, and electronic goods. Data on the oil price index is collected, since this series has been found to be highly correlated with economic growth in a recent paper by Iyer and Sen Gupta (2019). Data is also included on key labor market indicators such as the unemployment rate and the aggregate labor force, although these statistics are available only from 2016 onward. We further collect data on vehicle sales in India and foreign tourist arrivals.

Last but not least, the monthly dataset includes time series that measure the impact of rainfall and climate: (i) the total amount of rainfall in India for any month; and (ii) the monthly deviation of rainfall from its trend level, which captures the impact on growth of weather shocks. All the quarterly and monthly indicators in the model are made stationary for the purposes of nowcasting, as we transform the time series that originally have unit roots by taking their year-on-year growth rates. This annual differencing procedure also takes care of any residual seasonality in the dataset, which is potentially useful since the national account series released by the Central Statistics Office are not seasonally adjusted.

VII. EMPIRICAL RESULTS

A. Estimation

The DFM is estimated recursively over a period beginning in January 2000 and ending in December 2018. The recursive scheme implies that the nowcasts of quarterly GDP growth are produced and evaluated over a sequence of data samples, where the first sample begins in January 2000 and ends in December 2009, and the last sample begins in January 2000 and ends in December 2018. At the beginning of each quarter, the model is estimated using data available at that point while holding the parameters fixed until the next quarter. Relative to single quarter evaluations, this recursive methodology allows for a more robust evaluation of the nowcasting capabilities of the framework since we effectively average over several quarters' predictions errors to produce the RMSE.

The DFM predictions are updated each time new data is released as the nowcasts are based on all available information at any given point of time. As in Luciani et al. (2015), we include two factors in the DFM and two lags in the VAR that governs the evolution of the factors, but we also undertake robustness checks by reducing and increasing the number of factors and lags from one to four. Various

versions of the DFM are estimated as we test different groups of macroeconomic and financial variables. The estimation results indicate that DFMs with two factors generally have the highest predictive power, as these models have lower RMSEs compared to those with more or less factors. This is not at odds with the literature, which suggests that a small number of factors suffice to generate effective forecasts and nowcasts (Stock and Watson 2002, Forni et al. 2003, Luciani et al. 2015).

B. Performance of the Dynamic Factor Model

We compare the nowcasts generated by the DFM with the predictions of RW and AR models of GDP growth. The RW model is generally considered a benchmark in the forecasting literature. It is also useful to compare the DFM predictions with an AR model of order two (AR2) of GDP growth given the high persistence in the Indian GDP series, and as in Luciani et al. (2015). We estimate several variants of the DFM based on different groups and orderings of variables. Table 1 reports the 1-, 2-, and 3-month ahead RMSEs associated with the forecasts and nowcasts of an RW model, an AR2 model, and the best-performing DFM.

Notably, the DFM outperforms the two competing models of growth. Looking at the prediction errors in the first month, the nowcast RMSE from the DFM is reduced by 31% and 42% compared to the AR and RW models, respectively. The DFM forecast RMSE is reduced by 25% and 40% compared to the AR and RW models, respectively.

The relative improvement of the DFM over the two benchmark models can be compared to the performance of the DFM applied to another fast-growing emerging market economy, Indonesia (studied in Luciani et al. 2015), over the similar time period of 2002–2014. While the variables used in each country are specific to their unique economic situations, the DFM's performance is comparable across the two studies, and indeed the prediction errors of the first month DFM nowcasts and forecasts in India are 5 to 10 percentage points lower than those in Indonesia.

Table 1: Root Mean Squared Error, 2000–2018

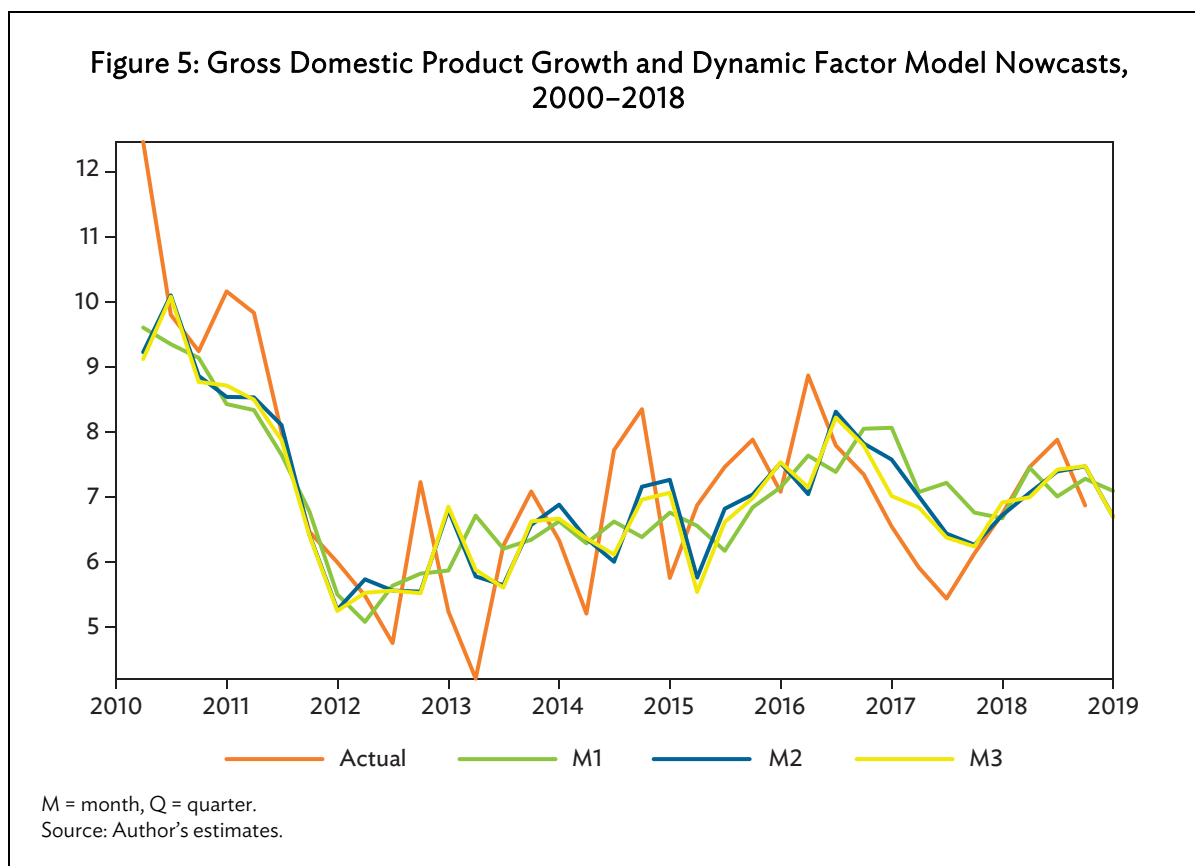
	Month	DFM	AR2	RW
Nowcast	1	1.130	1.646	1.932
	2	1.112	1.368	1.492
	3	1.105	1.368	1.492
Forecast	1	1.028	1.368	1.723
	2	1.087	1.374	1.696
	3	1.028	1.374	1.696

AR = autoregressive model of order two, DFM = dynamic factor model, RW = random walk.

Note: The DFM is estimated from January 2000 to December 2018, and the root mean squared error (RMSE) is the mean of RMSEs computed recursively over a sequence of quarterly data samples from January 2010 to December 2018.

Source: Author's estimates.

Figure 5 plots GDP growth from January 2010 to December 2018 along with the first, second, and third month nowcasts of growth based on the DFM. Note that the DFM is effective in capturing the turning points and tracking the evolution of growth. Figure A1 analogously plots GDP growth along with the first, second, and third month DFM forecasts.



C. Key Predictive Variables

The DFM in Table 1 includes 18 variables, of which six are quarterly and the rest are of monthly frequency. The quarterly variables include GDP and the components of GDP based on the expenditure approach—public and private consumption, investment, exports and imports. We also include the quarterly business confidence index, which captures corporate sentiment regarding future economic activity, as this improves the nowcast. Various variants of the DFM were tested including using the major components of GVA (since GVA approximated economic activity historically in India)—agriculture, industry, and services. This adjustment leads to larger prediction errors, however, suggesting that the components of the expenditure approach to GDP have more informational content.

We also tested quarterly variables in the dataset such as credit extended to the public and private sectors; the House Price Index; and external variables including the current account, external debt, net FDI, and net portfolio flows, but these do not add much informational content to the DFM nowcasts and forecasts. The predictive ability of the DFM is highest, therefore, when the quarterly variables are based on the expenditure approach to GDP while controlling for corporate sentiment in India. Versions of the DFM were also tested with more than two factors, but these led to larger prediction errors. Furthermore, around 45 monthly variables representative of the Indian economy, as described in the previous data section, were estimated in the DFM. Through an iterative procedure, we selected a final set of monthly variables, as described below, with the highest predictive power for GDP growth in India.

The specified DFM includes 12 monthly variables that enhance the predictive ability of the framework. As these series are of higher frequency than GDP, the DFM revises its growth projections as each monthly series is released. Interestingly, several indicators that were found to be effective in forecasting GDP growth in the Bayesian VAR framework in Iyer and Sen Gupta (2019) also enhance the predictive power of the alternatively specified DFM. These include the repo rate, the primary monetary policy instrument of the RBI, the oil price index, the monetary base, and the CPI. The CPI is better able to predict economic growth than the Wholesale Price Index as in Iyer and Sen Gupta (2019), due to reasons that include the switching of RBI from a multiple indicators approach to CPI inflation targeting in recent years.

Table 2: Data Release Dates for the Variables in the Dynamic Factor Model

Frequency	Indicator	Release Date
Quarterly	Gross domestic product	Lag of 2 months
	Total consumption	Lag of 2 months
	Investment	Lag of 2 months
	Exports	Lag of 2 months
	Imports	Lag of 2 months
	Business Confidence Index	Lag of 2.5 months
Monthly	Repo rate	Lag of 0 days
	Cash reserve ratio	Lag of 2 months
	Consumer Price Index	Lag of 12 days
	Narrow money	Lag of 2 weeks
	National Stock Exchange Index	Lag of 0 days
	Commercial bank credit	Lag of a month
	Commercial bank investments	Lag of a month
	Vehicle sales	Lag of 5 days
	Oil Price Index	Lag of 0 days
	Petroleum imports	Lag of 2 weeks
	Total rainfall	Lag of a day
	Deviation of rainfall from mean	Lag of a day

Sources: Central Bureau of Statistics; Reserve Bank of India; Ministry of Statistics and Programme Implementation; Society of Indian Automobiles; Ministry of Commerce; Centre for Monitoring Indian Economy; Author's estimates.

Other monthly variables with high predictive ability include the cash reserve ratio and especially key financial indicators such as the NSE index, total credit extended by the banking system, and commercial bank investments. This underscores the importance of macrofinancial linkages in India and the high informational content for economic growth of commercial bank credit and investments. Vehicle sales and imports of petroleum products also add predictive power to the DFM. It is interesting that oil prices and petroleum imports are significant variables—the correlation between oil and economic growth could arise due to India's extreme oil import dependence. India is among the top importers of crude oil in the world, and over a fourth of imports are oil imports. The release dates for the series included in the DFM are reported in Table 2.

D. The Role of Rainfall

A key finding of this study is that rainfall has high predictive content for economic growth. Including rainfall in the model leads to a reduction in the prediction errors, and this result holds robust to several changes in the estimation and out-of-sample forecasting periods, factors and lags in the DFM, and groups of other variables included in the framework. The importance of rainfall is, to the best of our knowledge, the first such result in the nowcasting literature. We include two monthly series on precipitation in the DFM: (i) the total rainfall in India in any given month and (ii) the monthly deviation of rainfall from its trend level, which captures the impact on growth of weather shocks. The result that including rainfall in the model increases nowcasting accuracy adds to the new climate-economy literature that correlates rainfall and climate with economic activity (see Dell, Jones, and Olken [2014] for a review). Table 3 replicates Table 1 but without rainfall as an explanatory variable for GDP growth. Note that the nowcast and forecast errors are consistently higher in the DFM without rainfall.

Table 3: Root Mean Squared Error, Dynamic Factor Model without Rainfall, 2000–2018

	Month	% Loss in DFM Accuracy	DFM	AR2	RW
Nowcast	1	9	1.231	1.646	1.932
	2	2	1.139	1.368	1.492
	3	3	1.133	1.368	1.492
Forecast	1	10	1.133	1.368	1.723
	2	5	1.144	1.374	1.696
	3	7	1.101	1.374	1.696

AR2 = autoregressive model of order two, DFM = dynamic factor model, RW = random walk.

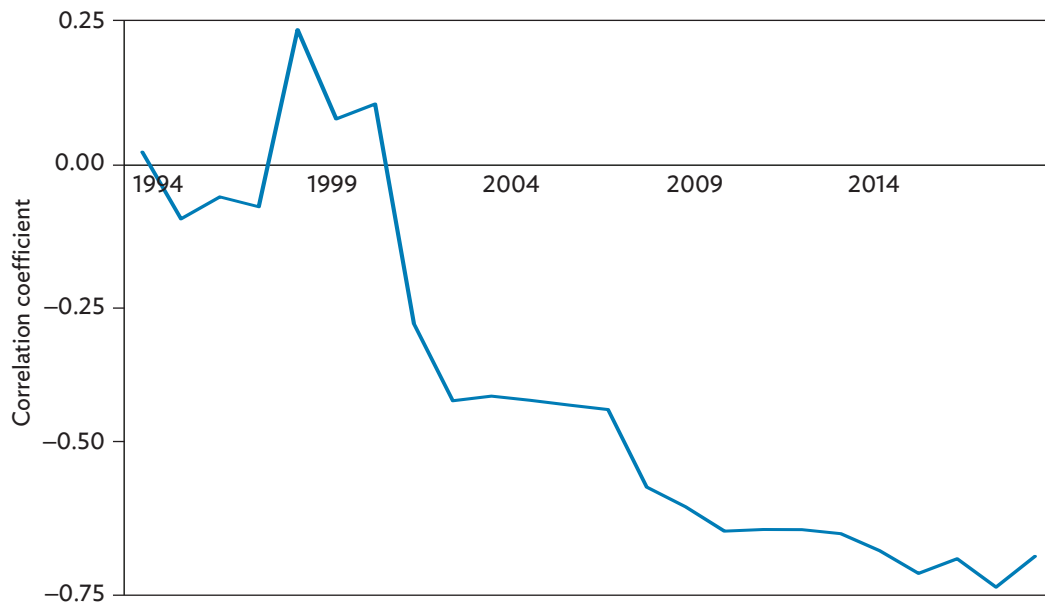
Note: The DFM is estimated from January 2000 to December 2018, and the root mean squared error (RMSE) is the mean of RMSEs computed recursively over a sequence of quarterly data samples from January 2010 to December 2018.

Source: Author's estimates.

The predictive significance of rainfall for economic activity is not surprising in light of India's high dependence on the agriculture sector. Nearly half of the Indian workforce is employed in this sector. Furthermore, farming is water intensive, and due to the relative inefficiency and irregularity of water supply in India, the majority of agricultural yields directly depend on rainfall (World Bank 2018). India's rank among the most water-stressed economies in the world coupled with its economically significant agriculture sector together help explain the high predictive content that rainfall has for economic growth. Our results corroborate empirical studies by Virmani (2006), Gadgil and Gadgil (2006) and Nomoto (2016), which all find that rainfall has a significant impact on economic activity in India, and that a channel through which this link arises is the effects of precipitation on agricultural productivity.

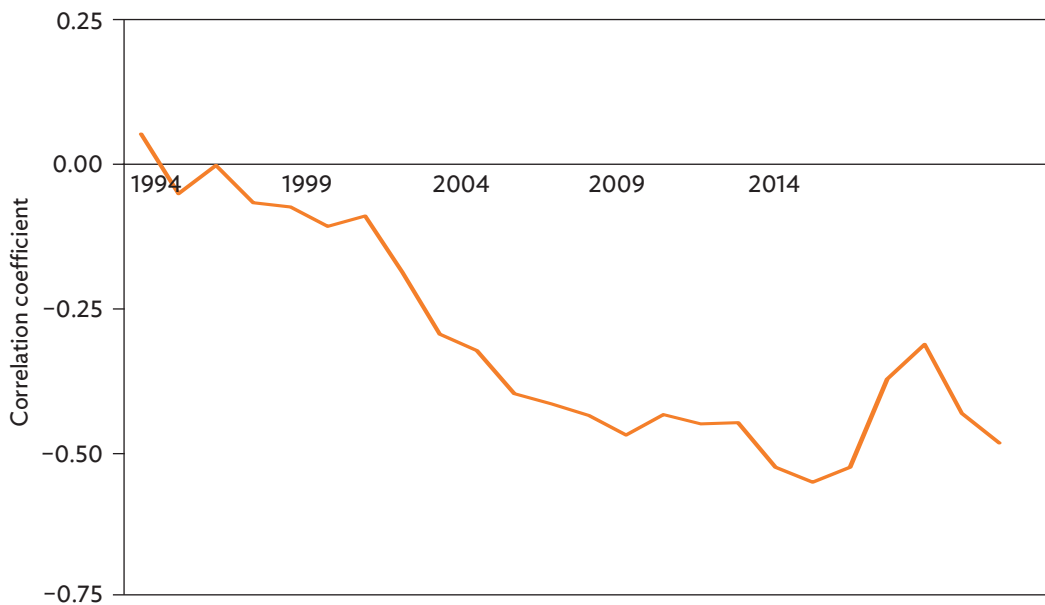
Figure 6 outlines the recursive correlation between absolute deviation of rainfall from normal and food production growth during the previous 2 decades. We focus on the absolute deviation of rainfall from normal as both scanty and excessive rainfall have a deleterious impact on food production growth. Figure 2 shows that the correlation is mainly negative and has intensified in recent years implying that deviant rainfall has been associated with lower food production compared to earlier years. A similar pattern emerges when we evaluate the relationship between rainfall deviation and private consumption growth although it remains weaker compared to food production growth (Figure 7).

Figure 6: Recursive Correlation between Absolute Deviation of Rainfall from Normal and Food Production Growth



Source: Economic Outlook Database, Centre for Monitoring Indian Economy. <https://economicoutlook.cmie.com/> (accessed 25 April 2019).

Figure 7: Recursive Correlation between Absolute Deviation of Rainfall from Normal and Private Consumption Growth



Source: Economic Outlook Database, Centre for Monitoring Indian Economy. <https://economicoutlook.cmie.com/> (accessed 25 April 2019)

E. Improved Stabilization Policies in India

It is interesting to assess whether the predictability of Indian growth has varied over time. Higher predictability in more recent times would suggest that stabilization policies have been effective. To assess the performance of the DFM during an earlier time period, we estimate the framework from January 2000 to December 2008. Growth in India was buoyant during this period, driven by domestic consumption and investment. The average growth rate exceeded 9% between the beginning of 2004 and the end of 2008. We end the estimation sample right before growth dropped near 0% in the beginning of 2009 when the Indian economy was roiled by the effects of the GFC. The average RMSE is computed recursively as before, with the first sample beginning in January 2000 and ending in December 2004, and the last data sample beginning in January 2005 and ending in December 2008.

Three findings emerge. First, the structural and stabilization policies enacted by the government since the liberalization of the 1990s appear to have positively affected economic activity. When the DFM is estimated over the earlier time period of 2000–2008, it performs worse than an RW (see Table 4). The RW model of growth has a 17% lower first-month nowcast RMSE compared to the specified DFM. On the other hand, over the 2000–2018 estimation period, the DFM significantly outperforms an RW, as indicated by a nowcast RMSE reduction of 42%. The decreased relevance of the RW model of growth over time suggests that economic growth in India has become more predictable, aided by targeted government policies geared toward structural change and stabilization.

Table 4: Root Mean Squared Error, 2000–2008

	Month	DFM	AR2	RW
Nowcast	1	2.508	2.447	2.138
	2	2.277	2.200	2.073
	3	2.222	2.200	2.073
Forecast	1	2.919	3.156	2.940
	2	2.837	2.856	2.631
	3	2.825	2.856	2.631

AR2 = autoregressive model of order two, DFM = dynamic factor model, RW = random walk.

Note: The DFM is estimated from January 2000 to December 2008, and the root mean squared error (RMSE) is the mean of RMSEs computed recursively over a sequence of quarterly data samples from January 2005 to December 2008.

Source: Author's estimates.

Second, we find that rainfall *consistently* has high informative content for economic growth in India. The predictive ability of rainfall holds robust to changes in estimation samples (as discussed here, as well as changes in the other variables included in the DFM). Including rainfall in the DFM continues to reduce the estimation errors for nowcasting and forecasting growth in the 2000s. Table 5 reports the RMSEs of the DFM without rainfall estimated from 2000–2008.

The DFM with rainfall leads to a relative improvement over the model without rainfall of around 10% in the first month of 2000s (Table 4). The analogous improvement is a bit lower at 9% when the model is estimated from 2000 to 2018 (Table 3). While rainfall continues to be highly informative, this finding makes sense in light of the Indian economy transitioning away from an agrarian model toward a more urbanized society over time.

Table 5: Root Mean Squared Error, Dynamic Factor Model without Rainfall, 2000–2008

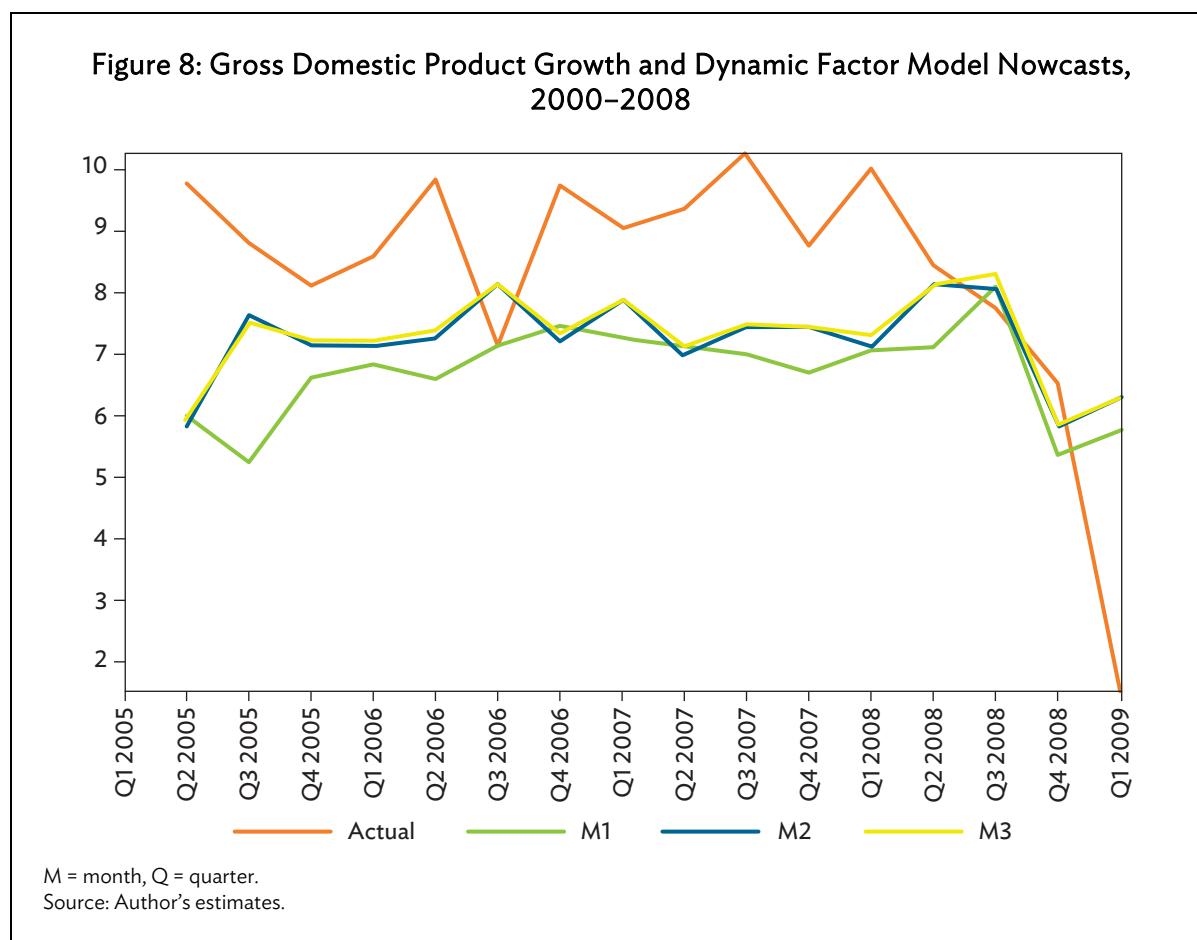
	Month	% Loss in DFM Accuracy	DFM	AR2	RW
Nowcast	1	10%	2.770	2.447	2.138
	2	5%	2.393	2.200	2.073
	3	7%	2.370	2.200	2.073
Forecast	1	8%	3.165	3.156	2.940
	2	5%	2.987	2.856	2.631
	3	7%	3.014	2.856	2.631

AR2 = autoregressive model of order two, DFM = dynamic factor model, RW = random walk.

Note: The DFM is estimated from January 2000 to December 2008, and the root mean squared error (RMSE) is the mean of RMSEs computed recursively over a sequence of quarterly data samples from January 2005 to December 2008.

Source: Author's estimates.

Figure 8 plots GDP growth from January 2005 to December 2008 along with the first, second, and third month nowcasts of growth based on the DFM. The first, second, and third month DFM forecasts can be found in Appendix Figure A2.



VIII. CONCLUSION

This study seeks to nowcast GDP growth in India on a quarterly basis using a DFM. DFMs have been often used in the literature for nowcasting economic growth as they are powerful estimation tools that capture the comovement among time series and can handle mixed-frequency data. The model is estimated from January 2000 to December 2018 using 18 variables from the real, monetary, financial, and external sectors that are specific to the Indian economy. The monthly variables include macrofinancial indicators such as commercial bank credit, commercial bank investments, and the NSE index; monetary policy indicators including the repo rate and the cash reserve ratio, the CPI; money, oil price index, imports of petroleum, vehicle sales, rainfall; and the deviation of rainfall from its mean in any given month. The quarterly variables include a Business Confidence Index and the components of GDP calculated using the expenditure approach.

This study provides a toolkit for nowcasting GDP growth in India. A key finding is that rainfall has high predictive content for economic growth. This, to the best of our knowledge, is the first such result in the nowcasting literature. The finding makes sense given India's unique reliance on rainfall. Water scarcity is a pressing problem in India, and with half the workforce employed in the agriculture sector, precipitation patterns assume special significance. We also find that the predictability of GDP growth in India has increased over time, suggesting that the structural and stabilization policies enacted by the Indian government have had positive effects.

The results of this study have a couple of policy implications. Given the high predictive power that rainfall has for economic growth, it would seem that policy makers should consider increasing the general availability and stability of water supply in India. Irrigation systems in India are still not well developed, and our findings corroborate policy recommendations by the Asian Development Bank (ADB) and other organizations to build efficient and climate-resistant irrigation networks in India. Attempts to do so are already underway through partnerships by the Indian government with various nongovernmental and international organizations. ADB, for instance, loaned \$375 million in August 2018 to the Madhya Pradesh government to develop 125,000 hectares of new irrigation networks through the Madhya Pradesh Irrigation Efficiency Improvement Project.

There is typically a trade-off between equity and efficiency in terms of using scarce fiscal resources to promote development needs versus spurring economic growth. In this case, however, the ADB project is expected to contribute toward doubling farmer's incomes, and, as this study finds, stable water supply can also help predict GDP growth. India is among the world's most water-stressed countries, a situation that is exacerbated by a very economically significant agriculture sector. These facts together help explain the high informational content that rainfall for GDP growth. Improving the stability and efficiency of water supply in India appears to be a useful way for policy makers to achieve the dual objectives of promoting economic growth and mitigating poverty.

APPENDIX

Table A1: Data Sources

Indicator	Source
Gross domestic product	Ministry of Statistics and Programme Implementation (MOSPI), Government of India
Total consumption	MOSPI, Government of India
Investment	MOSPI, Government of India
Exports	MOSPI, Government of India
Imports	MOSPI, Government of India
Business confidence index	Reserve Bank of India (RBI): Handbook of Statistics on Indian Economy
Repo rate	RBI: Weekly Statistical Supplement
Cash reserve ratio	RBI: Weekly Statistical Supplement
Consumer price index	RBI: Handbook of Statistics on Indian Economy
Narrow money	RBI: Handbook of Statistics on Indian Economy
National Stock Exchange index	RBI: Handbook of Statistics on Indian Economy
Commercial bank credit	RBI: Handbook of Statistics on Indian Economy
Commercial bank investments	RBI: Handbook of Statistics on Indian Economy
Vehicle sales	Society of Indian Automobile Manufacturers
Oil price index	Federal Reserve Economic Database, Federal Reserve Bank of St. Louis
Petroleum imports	Ministry of Commerce, Government of India
Total rainfall	Central Bureau of Statistics, Government of India
Deviation of rainfall from mean	Central Bureau of Statistics, Government of India

Sources: Authors.

Figure A1: Gross Domestic Product Growth and Dynamic Factor Model Forecasts, 2000–2018

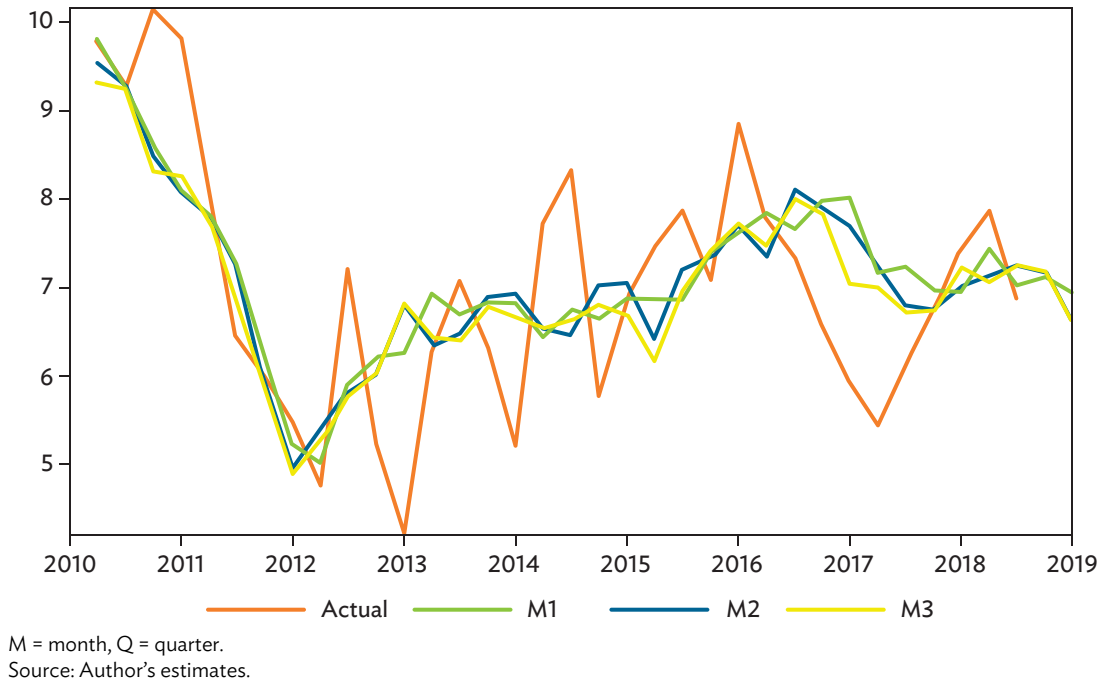
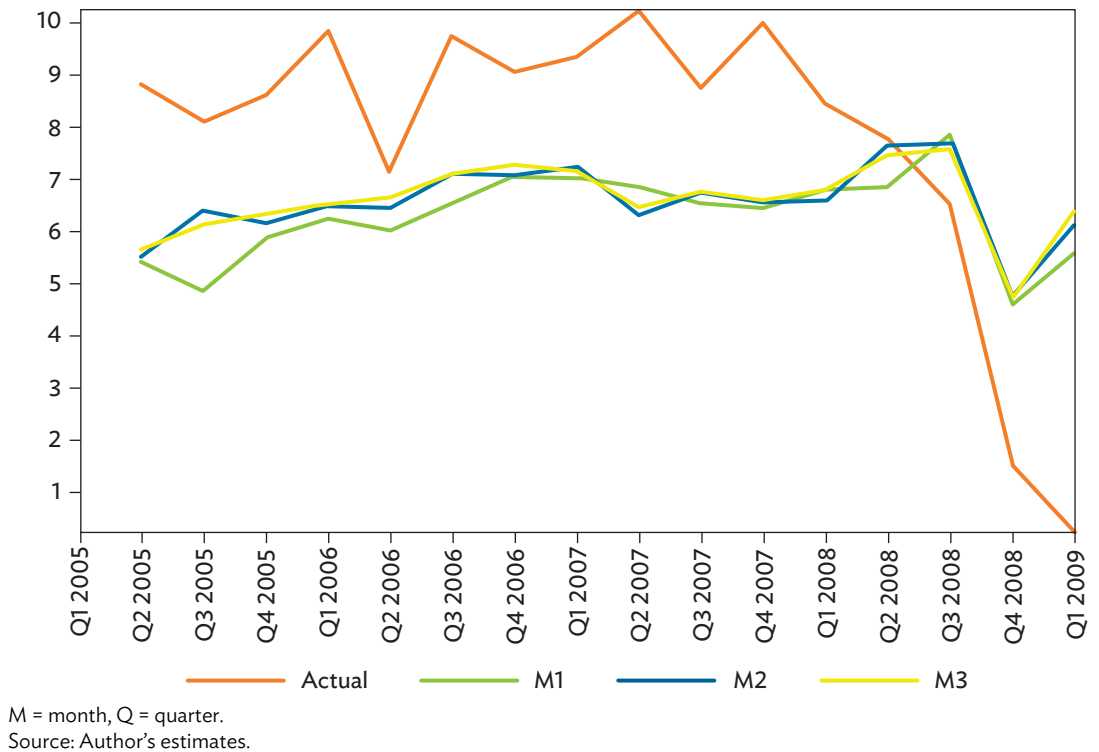


Figure A2: Gross Domestic Product Growth and Dynamic Factor Model Forecasts, 2000–2008



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Nowcasting Economic Growth in India

The Role of Rainfall

“Nowcasting” uses high frequency data to generate estimates of gross domestic product (GDP) growth, which are otherwise published with a lag. It helps policy makers and market participants overcome decision-making difficulties when official statistics on key variables like economic growth are delayed. This paper develops an econometric framework specific to the Indian economy and nowcasts quarterly GDP growth in India. It finds that rainfall has high predictive content for GDP growth, although this predictive content has declined slightly over time. It also finds that structural and stabilization policies enacted since the 1990s have increased the resilience of India to economic shocks.

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