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Determinants of Total Factor Productivity Growth in India

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Abstract

Purpose: The paper identifies the structural determinants of total factor productivity (TFP) growth in India between 1990 to 2019. **Design/Methodology/ Approach:** To examine the drivers of TFP growth at the aggregate level, ARDL models are used, whereas for identifying the sectoral level determinants, panel pooled group mean estimation methods suggested by Peseran et al. (1999) and 2SLS-IV approaches are used. **Findings:** The empirical analysis suggests at the economic level, a significant portion of the variation of aggregate TFP growth is explained by idiosyncratic shocks like deviations in rainfall, and exogenous global factors like global GDP growth rates. Public investment in infrastructure, an increase in the share of ICT capital in aggregate fixed capital, and improved global exposure through higher exports and inflows of foreign direct investment (FDI) are also associated with increased TFP growth. At the sectoral level, we find that productivity growth in the input-producing sectors and improvements in labour qualities are associated with higher TFP growth in all the sectors in India. Capital deepening is associated with improved TFP growth in manufacturing and market services. **Originality/Value:** To the best of our knowledge, this is the first attempt to empirically estimate structural determinants of TFP growth in India using India KLEMS and other nationally representative official data sources.

Keywords

India KLEMS, TFP, ARDL Model, 2SLS IV, Panel Data

1. Introduction

India witnessed a slowdown in its economic growth even before the COVID-19 pandemic hit the economy (Dev & Sengupta, 2020; Gupta & Tyagi, 2022; Goldar, 2022). The growth slowdown was accompanied by a sharp decline in the growth rate in total factor productivity (TFP), a broad measure of technological change, and aggregate efficiencies in the economy (India KLEMS, 2021). At the sectoral level, aggregate TFP growth was mainly supported by non-market activities such as public administration, defence, education, and social works, whereas TFP growth in market-based activities in industries and services sectors decelerated sharply, often registering negative growth. This raises doubt about the sustainability of aggregate TFP growth in India since the TFP growth driven by market-based sectors is observed to be higher than that of non-market-based sectors (RBI, 2022). Further, during the country's high growth phase between 2003-04 and 2007-08[1], India's growth was primarily driven by growth in the factors of production, mainly the stock of capital, while the productivity growth measured by the growth in TFP explained only about 15 percent of India's aggregate GDP growth. Globally, the evidence suggests that robust growth in GDP, in the long run, is supported by sustained growth in TFP (Solow, 1956; Klenow & Rodriguez-Clare, 1997; Hall & Jones, 1999). In the light of the above evidence, this paper examines the structural determinants of TFP growth in India.

Structural determinants of TFP growth are those macroeconomic variables that are either directly a part of the production function or directly associated with the production processes. Some variables that we may regard as the structural factors driving TFP growth are the following: capital deepening measured by growth in the stock of fixed capital (since new investments make it possible to bring in new technology as technological advances are often embodied in capital goods); growth in labour quality; growth in the unit cost of capital; input use intensity measured by the ratio of values of intermediate input and GVA; participation in the global value chains (GVCs) and international trade; use of information and communication technology (ICT); research and development expenditure; and foreign direct investment.

This paper aims to provide empirical estimates of the influence of these potential determinants of TFP growth in the Indian economy. An analysis at the aggregate economy level is undertaken first, following which an analysis of determinants of TFP is undertaken for the major sectors of the Indian economy, *viz.* agriculture, manufacturing (split into two parts), infrastructure industries, financial services, other marketed services, and non-marketed services since 1990. For the latter part, a panel data set for seven sectors stated above between 1991 and 2018 is used.

The paper is organized as follows. Section 2 contains a brief survey of existing

[1]India's national accounts data are published according to the financial years. For instance, the financial year (FY) 2000-01 would represent a period between April 2000 and March 2001. For simplicity, however, refer to FY 2000-01 as the year 2000, as it covers nine months from the calendar year 2000, as compared to only three months from the year 2001. We follow this convention throughout this paper.

literature in this area. Section 3 is devoted to an analysis of the determinants of TFP growth of the Indian economy at the aggregate level. Section 3 presents such an analysis at the sector level. Section 4 summarizes and concludes.

2. Review of Literature

A growing body of literature finds evidence that productivity growth is positively related to higher general investment rates, especially in investments in information and communications technologies (ICT). Kumar and Robert Russell (2002) decompose labour productivity into technological change, technological catch-up and capital accumulation to find that productivity growth is primarily driven by capital deepening. Jorgenson and Stiroh (2000) and Oliner and Sichel (2000) suggest that investment in ICT and technological progress in high-tech industries played an important role in driving TFP growth in the US. Jorgenson and Stiroh (2000) also distinguish between the heterogeneity of capital inputs used in the production process and acknowledge that a proper adjustment in the measurement of capital services in the presence of ICT is crucial for an appropriate understanding of TFP growth in the long run. In other words, they underscore the higher importance of ICT in promoting TFP growth over non-ICT capital. A review of the literature on the relationship between ICT capital and productivity by Cardona et al. (2013) suggests that the majority of the empirical studies support a positive and significant effect of ICT on productivity.

Alongside the stock of and composition of capital stock, the quality of the labour force is found to be an important factor for sustained growth in productivity (McGowan et al., 2015). Dieppe (2021) suggests that a better-educated and healthier workforce contributes more to technological advances and the absorption of new technologies in a country. Benhabib and Spiegel (2003) note that human capital influences technological progress and thereby enabling a higher rate of "catch-up". Maestas et al. (2016) find that the age composition of the labour force has an effect on productivity, and countries with a high share of the young working-age population rapidly adopted new technologies. Klasen and Santos Silva (2018) and Gallen (2018) note that improved earning opportunities for women lead to an increase in human capital. Studies by De Jong and Tsiachristas (2008) and Loko and Diouf (2014) find that increased participation of women in the workforce increases TFP gains.

While most of the literature looks at the determinants of TFP in cross-country settings, there is limited research on the drivers of TFP growth for India at the macro level. Some firm-specific studies that have looked into the drivers of productivity for manufacturing sectors (De & Nagaraj, 2013; Dougherty et al., 2009) find low firm turnover, a predominance of small-scale firms, and labour market distortions negatively affect manufacturing plants' productivity. Pradhan and Barik (1999) provide evidence on similar lines. Bhaumik et al. (2006) find that pro-competitive reforms and liberalisation of entry barriers have a strong positive effect on productivity. The contribution of trade liberalization to TFP growth in Indian manufacturing has been shown in firm-level studies by Topalova and Khandelwal (2011) and Goldar et al. (2020). It may be added here that there have been several studies that have used cross-industry panel data to study the determinants of TFP in Indian manufacturing (for example, Goldar & Kumari, 2003; Das, 2016). However, as mentioned earlier, there is a lack of research that looks into sector-level determinants of productivity encompassing the economy. To the best of our knowledge, a macro-study encompassing all sectors is almost non-existent, largely due to the unavailability of comparable estimates of TFP, labour quality and capital stocks. Previous studies either focused on a particular sector or mostly relied on labour productivity due to the unavailability of comparable TFP estimates at the all-India level. Studies based on the available periodic surveys of enterprises in India had mostly covered the formal sector of the economy. The more recently available India KLEMS data has provided consistent and comparable estimates of TFP and factor inputs for 27 activities encompassing the whole of India for the first time. Based on the India KLEMS data, our paper builds evidence on the impacts of physical and human capital on TFP growth for the Indian economy, by accounting for the sectoral heterogeneity. To the best of our knowledge, this is the first attempt at estimating these impacts across all sectors of the Indian economy, viz. agriculture, industries and services.

In the productivity literature, there are additional factors that are found to be significantly impacting TFP growth alongside human and physical capital. These include research and development (R&D) activities (Huergo & Jamandreu, 2004; Coe et al., 2009; Hall, 2011; McGowan et al., 2015), participation in trade and global value chains (GVCs) (Hall & Jones, 1999; De Loecker, 2013; Alcalá & Ciccone, 2004; Bloom et al., 2016; Criscuolo & Timmis, 2018; Grossman & Rossi-Hansberg, 2008; Constantinescu et al., 2017), diffusion of foreign technologies through foreign direct investments (FDIs) (Griffith et al., 2004; Keller & Yeaple, 2009; Haskel et al., 2007), aggregate resource reallocations (Hsieh & Klenow, 2009; Melitz, 2003; McGowan et al., 2015), institutions (Isaksson, 2007; Kose et al., 2009; Malik et al., 2021) to name only a few. Due to certain data limitations, it has not been possible for us to include these variables in our empirical models as additional controls. First, although we develop macro-evidence for the impacts, we use a panel dataset consisting of seven broad sectors that cover the entire economy to account for any sectoral heterogeneity. Many of these factors, however, either do not apply to some sectors, or no consistent estimates are available at the sectoral levels. For instance, international trade and GVC participation are negligible for services activities that are not traded, such as the domestic wholesale and retail trade, hotels, restaurants etc. The nature of R&D activities, on the other hand, widely varies across different sectors and hence any single indicator for R&D would not be comparable across sectors. A large segment of service activities in India is undertaken by household enterprises where any measurable R&D activities are negligible. If we were to account for changes in these sector-specific macroeconomic scenarios, we had to restrict our study only to certain selected sectors, like most of the previous studies. Second, there is hardly any method by which one can attribute the development in physical and financial infrastructures and much of the institutional reforms to any specific sector. Now, while the inclusion of year-specific dummy variables would allow us to control for any domestic reforms and international shocks that might be invariant across sectors, the omission of other factors such as those discussed above could create some biases in our estimates. To avoid such issues, we use a two-stage least square instrumental variable (2SLS-IV) approach for our empirical estimates. We discuss the methodological details of the analysis based on panel data in Section 4.

3. Stylized Facts

The global productivity growth has slowed down since 2010, following only a brief recovery after the Global Financial Crisis (**Figure 1**). However, the productivity slowdown was widespread, and affected advanced, emerging market and developing economies. The global TFP growth declined from 1.5 percent in 2010 to −0.3 percent in 2019. The decline in TFP growth was much sharper in the case of the emerging and developing economies, where it contracted by about 1.0 percent in 2018 compared to an expansion of 1.5 percent in 2010. Globally, the slowdown in productivity growth is attributed to weaker investment, tepid employment generation in developed economies, reduced global value chain participation, fading gains from the factor reallocation, etc., among other reasons (Dieppe, 2021)[2]. In contrast, India witnessed only a moderate decline in TFP growth in recent years. In India, between 2010 and 2016, aggregate TFP grew by over 3 percent annually on average, barring some slowdown in 2012. However, TFP growth in India has also moderated since 2017, though the average growth rate from 2010 to 2019 is estimated at 2.2 percent, which is much higher than the emerging market average growth of −0.3 percent for the same period[3] (**Figure 1**).

The TFP growth accounted for nearly 30 percent of India's aggregate GDP growth between FY 2014 and FY 2018. In fact, acceleration in GDP growth during the period FY 2014 to FY 2017 can be attributed to the increase in TFP growth, when contributions from both capital and labour declined (**Figure 2**). In contrast, reflecting the deceleration in aggregate GVA growth since FY 2018, as also there has been a notable slowdown in TFP growth, and a higher contribution from labour.

The time series on the economy-level TFP growth rates obtained after applying the Hodrick-Prescott time-series filter is shown in **Figure 3** along with the growth rates in the aggregate economy real gross value added (GVA). From an

[2]Alistair Dieppe (2021). *Global Productivity: Trends, Drivers and Policies.* Advance Edition. Washington, DC: World Bank.

[3]TFP being a residual of growth accounting, it is more appropriate to refer to period averages rather than TFP estimate of any single year.

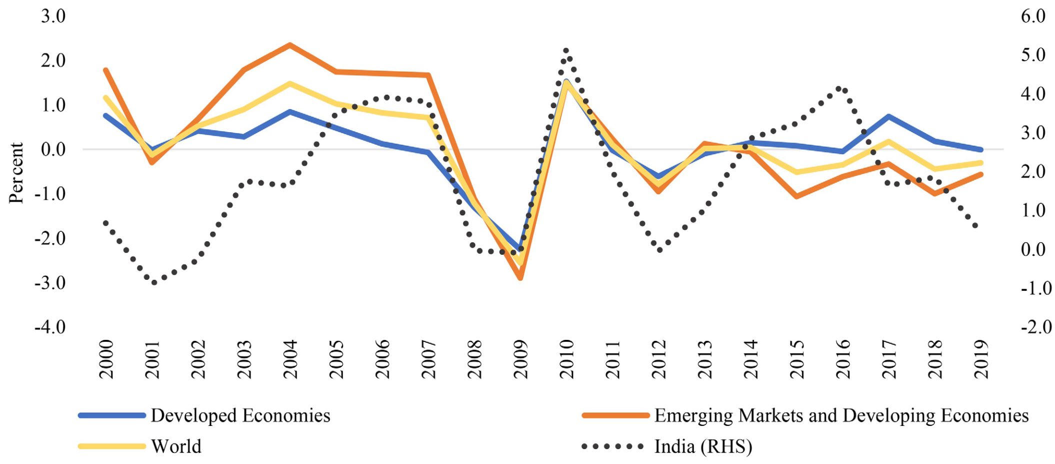

Figure 1. Total factor productivity growth-global trends. Note: Years refer to calendar year.

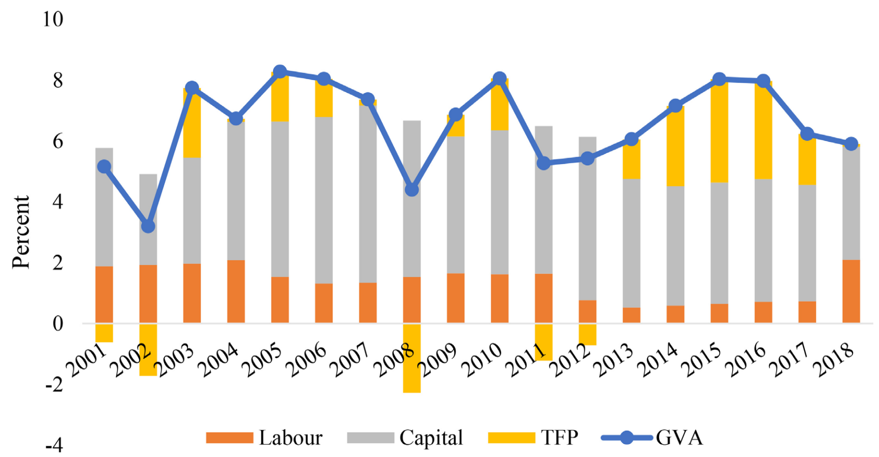

Figure 2. Decomposition of GVA growth in India. Source: Authors' estimates based on India KLEMS.

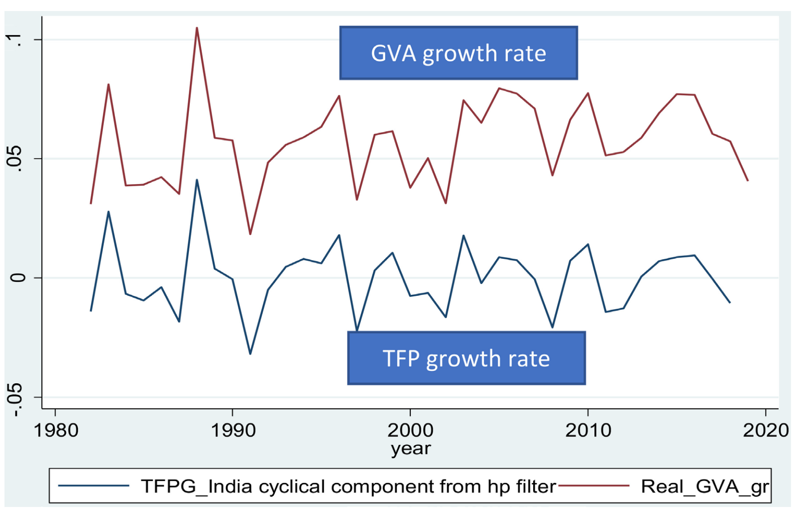

Figure 3. TFPG, Indian economy, 1982-2018, after applying the Hodrick-Prescott time-series filter, and the growth rate in real GVA of the Indian economy. Source: Authors' computations.

examination of the chart, we may conclude that the TFP growth rate of the Indian economy has been moving in a pro-cyclical manner[4]. The procyclical nature of TFP growth in India has been noted earlier in the literature (see, for example, Srivastava & Sengupta, 2000). However, this is not unique to India—such cyclicity in TFP growth has been noted in some other studies as well undertaken for other countries (see, for example, Miyagawa et al., 2005; Field, 2010).

The important question is whether the observed pro-cyclicity is merely a statistical artefact or if there are some important factors underlying it. In the study of Field (2010) for the US for the period 1890-2004, it is argued that pro-cyclicity principally emerged from demand shocks interacting with capital services which were relatively invariant over the cycle. Possibly, variations in demand could explain in part the pattern seen for India, the analysis of which is however not attempted in the paper, since the paper is focused on structural determinants of TFP growth. Although that is the case, an outright omission of any demand-side variable would certainly result in bias in our estimates. Therefore, we have proxied the demand side parameters broadly by two variables, which are largely exogenous to TFP growth in India. These are 1) deviation of annual rainfall from the long-period average and 2) annual growth rate of GDP in OECD economies.

A broad sectoral analysis suggests that a relatively higher TFP growth in recent years was mainly driven by non-market services such as public administration, defence, education, social works and related services (**Figure 4(a)**). TFP growth in non-market services remained particularly high in the years after the GFC. In recent years, viz. FY 2016 and FY 2017, TFP growth in agriculture was also high, which contributed to higher aggregate level TFP growth. In contrast, between FY 2008 and FY 2014, the sectors which are mainly driven by market forces viz. manufacturing and market services, witnessed either negative or very low TFP growth. In FY 2019, TFP growth in non-market services remained positive, while TFP growth in other sectors turned negative. The recent trend, therefore, raises some doubt about the sustainability of aggregate TFP growth, since it is mainly driven by non-market-based activities that are largely owned by public-sector entities. **Figure 4(b)** suggests that TFP growth from market-driven sectors (i.e. when the non-market services and agriculture are excluded) has generally remained higher than the aggregate TFP growth during the high GDP growth phase between FY 2002 and FY 2007. In contrast, during a relatively lower GDP growth phase following the GFC, the growth in aggregate TFP remained higher than those in market-driven sectors. This pattern suggests that during phases of economic slowdown and uncertainty outlook, aggregate TFP growth is largely driven by non-market services where the public sector and agriculture dominate. On the other hand, the contribution of these sectors to aggregate TFP growth often declines during the period of economic boom.

[4]There have been a number of studies on business cycles in India. See, for example, Dua and Banerji (2012), Pandey et al. (2018), and Misra and Chatterjee (2021).

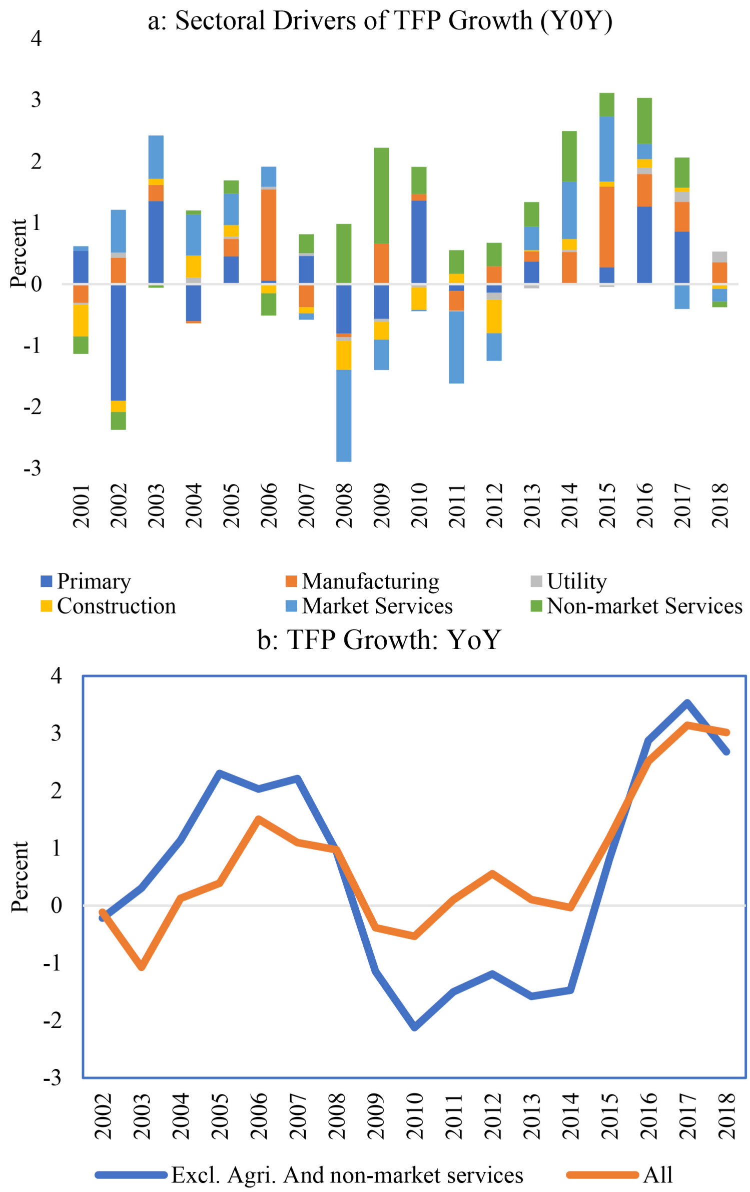

Figure 4. Sectoral drivers of TFP growth (YoY) in India. Source: Author's calculations based on India KLEMS.

Thus, two clear patterns emerge over the medium term as regards the TFP growth in India. They are a higher growth in TFP for India amid the general slowdown across the globe and divergences in TFP growth patterns between market and non-market sectors. These patterns require an examination of the structural factors behind TFP growth. We carry out our empirical assessment in this regard in the following sections.

4. Data and Methodology

The empirical methodology in this paper is divided into two parts. First, we look at the maximum possible set of determinants of TFP growth based on the available literature and the availability of sufficient data for India in a time series set-up. In this case, all the variables are taken at the all-India aggregate level over the last few decades. In addition, we also use panel data, where we can control for some unobserved factors using the period and industry-specific dummy variables. Those factors in a time series model might be correlated with TFP growth as well as its determinants. Despite the advantages of panel data techniques, the time series estimates are also useful to understand the effects of those factors that are aggregate in nature which means we cannot have their values specific to the industries that we consider for the panel data. Given this, we conduct the panel data analysis following the time series exercise.

The results of the time-series analysis are presented in Section 5.1 of the paper and the results of sector-level panel data analysis are presented in Section 5.2 of the paper. Section 5.1 is divided into two parts: Section 5.1.1 presents the results based on only two explanatory variables, and Section 5.1.2 expands the analysis by considering a larger number of explanatory variables.

4.1. Time Series Model

For the time series models, India's aggregate TFP growth rate is used as the dependent variable, and the following variables are used as explanatory variables:

1) Deviation of annual rainfall from the long-period average (LPA),

2) Annual growth rate in GDP of OECD countries,

3) Change in the share of ICT capital assets in the stock of all fixed assets,

4) TFP growth rate in infrastructure industries,

5) Annual growth rate in trade-weighted TFP for India's 34 merchandise trade partners,

6) Net cumulative public investment in infrastructure normalized by GDP, and

7) Ratio of cumulative FDI in the past five years to GDP.

Since the impact of FDI on the economy-level productivity may take time to take effect, especially considering the productivity spill-over effects, the cumulative FDI of the previous five years has been taken.

For the initial part of the time-series analysis, we have done the unit root test for 1) the TFP growth rate of the Indian economy, 2) the deviation of rainfall from the long period average (hereafter called rainfall deviation), and 3) the growth rate in GDP of OECD countries. The ADF test and Phillips-Perron test have been conducted in the study. Based on the test results, it may be inferred that all three variables are integrated of order zero, i.e. these are I(0) (see **Table A1** in **Appendix**).

The analysis of the determinants of TFPG has been done by applying the auto-regressive distributed lag (ARDL) model. To outline briefly the econometric methodology, let TFPG denote the dependent variable (TFP growth rate in the Indian economy in this study) and X denote the vector of explanatory variables.

The model may be written as (see Kripfganz & Schneiderand, 2022, among others):

$$\text{TFPG}_t = \alpha + \lambda t + \sum_{i=1}^{p} \phi_i \text{TFPG}_{t-i} + \sum_{j=0}^{q} \beta_j X_{t-j} + \eta' Z_t + u_t \quad (1)$$

In this equation, t is the time subscript and trend variable, and u_t denotes the error term. TFPG in year t depends on TFPG in the previous years (up to p lags allowed). It also depends on the current and lagged values of the explanatory variables contained in vector X. A trend term is allowed in the model. Also, a set of exogenous variables denoted by Z is included in the model. These variables have the predictive power to explain the short-term fluctuations in TFPG but do not affect its equilibrium path. Associated with the above equation, there is an error-correction model (see Kripfganz & Schneiderand, 2022, among others). From the error-correction model, the long-run coefficients of the explanatory variables and the adjustment coefficient may be derived (for details, see Kripfganz & Schneiderand, 2022, among others). To estimate the model described above, initially, the rate of TFP growth has been taken as a function of the deviation in rainfall and the OECD GDP growth rate. In view of the observed trends in 15-year interlocking period correlation coefficients (see **Figure 5**, presented later), the period chosen for the analysis in this section is 1982-83 to 2008-09 instead of 1982-83 to 2018-19.

As mentioned above, the analysis based on time-series data is expanded to include several additional variables. For the variables used for this part of the analysis, unit root tests have been carried out. Augment Dickey-Fuller ture capital stock test shows that the variables TFPG_world and Infra_Inv (the ratio of infrastruc to GDP) are I(0), and the FDI-GDP ratio, ΔICT_ratio, and TFGP_infra (TFPG of infrastructure industries) are found to be I(1) (**Table A2** in **Appendix**). The

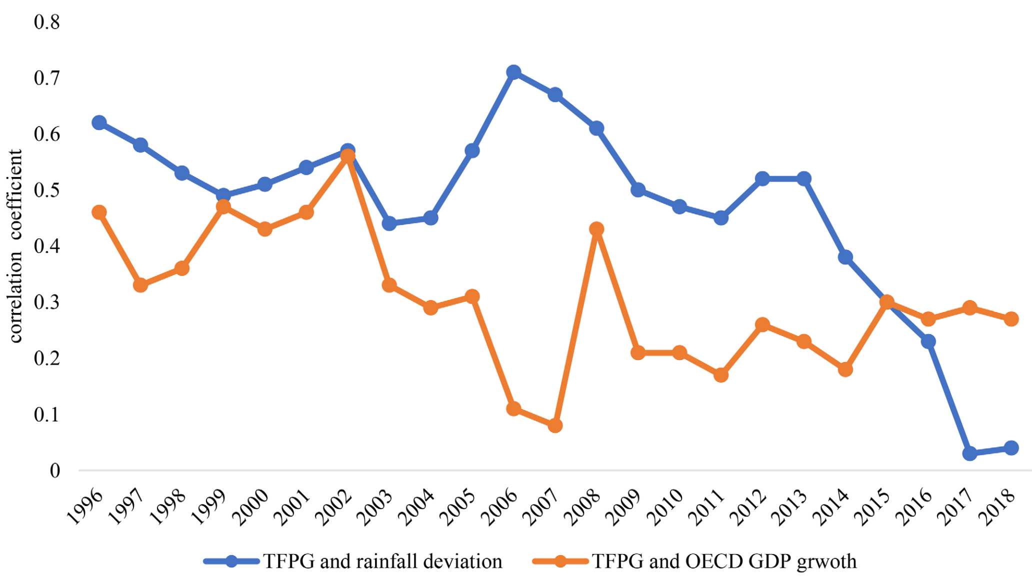

Figure 5. Correlation coefficients between TFPG and rainfall deviation and OECD GDP growth. Source: Authors' computations.

growth rate in GDP of OECD countries which is also included in this part of the analysis may also be taken as I(0) as indicated by the results in **Table A1** and the test results in **Table A2**. The fact that the explanatory variables are a mix of I(0) and I(1) makes the ARDL model an appropriate model to apply for econometric analysis.

As regards the dependent variable, namely the TFP growth rate of the Indian economy (TFPG_India), the results of the Augmented Dickey-Fuller test and Phillips-Perron test do not indicate that the variable is integrated of order zero. The test results are shown in **Table A3** in **Appendix**. Going strictly by the critical values according to the 1% level of significance, the variable may be treated as I(1). It may be pointed out here an ARDL model has been applied to analyze the determinants of TFP growth in the Indian economy in a study undertaken by Malik et al. (2021). In their study, the dependent variable is the growth rate of TFP in the Indian economy, and it is found to be integrated of order one, i.e. the variable is I(1) according to the Augmented Dickey-Fuller test and Phillips-Perron test.

The ARDL model requires that none of the variables should be I(2) or of higher order. This is not a problem here as the variables are found to be I(0) or I(1)—a mixture of I(0) and I(1) explanatory variables is acceptable. Note that the order of integration of the dependent variable of the model is not entirely clear from the test results. If it is treated as I(1) which seems justified, the model is applicable. If it is treated as I(0), then it appears to us that such a model will be justified if the explanatory variables that are I(1) are co-integrated. It is important therefore the estimated equation should be subjected to the Pesaran et al. (2001) bounds test, and the results should indicate the presence of co-integration.

The main source for the TFP growth rates in India for this analysis is the India KLEMS database version 2020. India KLEMS database provides annual estimates of TFP growth rates for 27 broad activities, known as the industries in India KLEMS. The database covers the entire Indian economy in both formal and informal segments in all the sectors, viz. agriculture, industries, construction and services. Apart from the estimates of TFP growth for 27 industries, the India KLEMS database also provides estimates of TFP growth at the all-India level, and broad sectoral levels, viz. agriculture, manufacturing and services. All these estimates are available at the annual frequencies for the financial years (FYs) since FY1980-81, which, for the sake of convenience, we denote simply by the starting year, say 1980, and so on. For the first part of our empirical analysis, we have used the all-India estimates of TFP growth rates provided by the India KLEMS database as our dependent variable between 1980 and 2018.

Data on rainfall have been taken from the economic and political weekly research foundation (EPWRF) databases. The long period average of rainfall for the country has been taken as 1182.8 mm based on data for the period 1901-2003 (Guhathukarata & Rajeevan, 2006). Data on the growth rate in GDP of OECD countries have been taken for a document of the World Bank on country-wise GDP growth rates. These are annual growth rates in GDP at market prices at constant local currency. Aggregates are based on constant 2015 prices expressed in the US dollar. The absolute change in the share of the value of ICT capital in all fixed capital measured in percentage points is computed from the Total Economy Database by The Conference Board. TFP growth rate in the infrastructure industry is a weighted average of TFP growth rates of the following three industries: 1) Mining and quarrying, 2) Electricity, gas and water supply, and 3) construction. The weights are based on the GVA of these industries. Net cumulative public investment in infrastructure has been computed by taking data on capital formation by the public sector in National Accounts Statistics. Cumulative net investment (at 2011-12 prices) from 1960 onwards has been computed for each year from 1980 onwards. This has been divided by GDP. The investments in the following industries are considered: 1) electricity, water supply and other utility services, 2) construction, 3) transport, and 4) communication.

In this empirical model, we have used the annual growth rate in merchandise trade-weighted TFP for India's 34 trade partners as an explanatory variable. First, we have identified 34 countries that accounted for the highest shares between 1990 and 2018 in India's total trade, comprising both exports and imports[5]. The aggregate TFP growth rates for these countries are available in the Penn World Table version 10.0. We have used the weighted average of these country-wise aggregate TFP growth rates from the Penn World Table 10.0 where we used the share of each country in India's aggregate merchandise trade for each year after 1990 as weights. For years before 1990, we have used the weights as of 1990. This weighted average TFP growth rate for India's top 34 merchandise trading partners is used as an explanatory variable in this part of the empirical estimations.

4.2. Analysis Based on Sector-Level Panel Data

For sectoral analysis, we use a panel data set across seven sectors as discussed in the previous section between 1991 and 2018, and regress annual growth rates of sectoral TFP on the following explanatory variables:

1) TFP growth rates in input-producing sectors,
2) Equipment to total assets ratio,
3) Exports,
4) Capital deepening,

[5]Countries and regions with their respective shares (percent) in India's trade (exports + imports) in parentheses are: USA (12.5), UAE (6.6), China mainland (6.3), Germany (5), UK (4.5), Japan (4.4), Belgium (4), Saudi Arabia (4), Hong Kong (3.2), Singapore (3.1), Switzerland (3.0), Australia (2.3), South Korea (2.3), Russia (2.3), Italy (2.2), France (2.1), Malaysia (2.1), Indonesia (2), Netherlands (1.7), Iran (1.6), Kuwait (1.6), South Africa (1.4), Bangladesh (1.1), Iraq (1.1), Thailand (1.1), Canada (1.0), Qatar (0.8), Sri Lanka (0.8), Taiwan region (0.8), Israel (0.7), Spain (0.7), Brazil (0.7), Egypt (0.6) and Vietnam (0.6). These countries and regions collectively accounted for more than 88 percent of India's trade (exports + imports) between 1990 and 2018.

5) Growth in labour quality and,

6) Growth in capital composition.

First, we performed a Hausman specification test for panel data following Hausman (1978). The results suggest that the following variables—the share of equipment to total assets, TFP in input producing sectors, and sectoral exports—are exogenous with respect to the TFP growth rates in the 7 sectors (**Table A4** in **Appendix**). The test, however, suggests that the growth in fixed capital, labour quality and capital composition are endogenous (**Table A5**). We found that these results are robust by adding each variable successively, and also jointly. Therefore, for the share of equipment in total assets, TFP growth rates in input producing sectors, and sectoral exports, we apply the ARDL-based Pooled Group Mean estimation method suggested by Peseran et al. (1999) for panel dataset with mixed order of integration. The long-run specification of the model is as follows:

$$\widehat{tfp_{k,t}} = \alpha + \beta * \widehat{tfp}_{k,t}^{in} + \gamma * eqstr_{k,t} + \gamma * \log\left(x_{k,t}\right) + u_{it} \quad (2)$$

where $\widehat{tfp_{k,t}}$ represents the growth rate of TFP for sector k at period t. The explanatory variables, $\widehat{tfp}_{k,t}^{in}$, $eqstr_{k,t}$ and $\log\left(x_{k,t}\right)$ represent the aggregate TFP growth rates in all the input producing sectors for the k^{th} sector, the share of equipment in the total value of fixed assets and the value of exports for the k^{th} sector, respectively.

For estimating the effects of growths in the stock of fixed capital, labour quality and capital composition, we use a 2SLS IV approach, since the Hausman (1978) test rejected the null hypothesis of no difference between a consistent estimator and a less consistent but more efficient for random effects estimator. In our empirical estimates, we regress the TFP growth on contemporaneous and one-year lagged growth rates in each of the following: capital stock, labour quality index and capital composition index. We use contemporaneous growth in intermediate input as the instrument for capital growth. The indices of labour quality and capital composition essentially capture the unit cost of these factors of production at their equilibria. Therefore, we tried to use some proxies for the exogenous variations in their demand functions as instruments. From this perspective, we have used lagged variations in the quantity of the factors, which are uncorrelated with the contemporaneous error term, as instruments. For example, for labour quality, we use the fourth lag of the labour-capital ratio as the instrument. For capital composition, we use the one-year lagged growth in capital stock as the instrument. **Table A6** in **Appendix** suggests the validity of these instruments. The regression coefficients from the chosen instruments are statistically significant and robust in different specifications. In the case of the input growth, we use only the second-year lag of the variable as a regressor to avoid any estimation biases arising due to its correlation with the error terms in the regression. In the regressions, we control for two-year lagged GVA growth rates in the sectors. Also, we use lagged TFP growth rates to control for any stochastic trend present in TFP growth. We also control for the unobserved sector and year-specific effects through dummy variables. The year effects would control for any unobserved effects including some global or all-India level policy changes that might impact all the sectors.

First, we run this model on a panel data set up consisting of 7 industries for the period between 1990 and 2018. In this case, the estimated coefficients would represent the economy-wise aggregate effects. The estimation model takes the following form:

$$\widehat{tfp_{k,t}} = \alpha + \sum_{l=1}^{3}\beta_l \widehat{tfp_{k,t-l}} + \sum_{l=0}^{1}\gamma_l \widehat{k_{k,t-l}} + \sum_{l=0}^{1}\delta_l \widehat{lq_{k,t-l}} + \sum_{l=0}^{1}\sigma_l \widehat{kq_{k,t-l}} + \mu \widehat{ii_{k,t-2}} + \pounds \widehat{va_{k,t-2}} + year_{FE} + sector_{FE} + u_{k,t} \quad (3)$$

where the variables *tfp*, *k*, *lq*, *kq*, *ii* and *va* represent the TFP, capital stock, labour quality, capital composition, intermediate inputs and the GVA, respectively. The notation ^ represents the growth rate over the previous year. The subscripts *t*, *k* and *l* represent year, sector and lags, respectively. $u_{k,t}$ represents the error term in the regressions.

Equation (3) provides an average effect of the explanatory variables on the TFP growth for the economy. However, depending on the nature of the underlying production function, these effects might be very different across sectors. To account for this heterogeneity, we have introduced the interaction of sector-specific dummy variables, except for agriculture, with each of these explanatory variables. In this case, agriculture serves as the reference sector. The coefficient without an interaction would represent the effects for the agriculture sector. The estimation equation becomes:

$$\begin{aligned}\widehat{tfp_{k,t}} = {} & \alpha + \sum_{j=2}^{6}\sum_{l=1}^{3}\beta_{j,l} \widehat{tfp_{j,k,t-l}} + \sum_{j=2}^{6}\sum_{l=0}^{1}\gamma_{j,l} \widehat{k_{j,k,t-l}} \\ & + \sum_{j=2}^{6}\sum_{l=0}^{1}\delta_{j,l} \widehat{lq_{j,k,t-l}} + \sum_{j=2}^{6}\sum_{l=0}^{1}\sigma_{j,l} \widehat{kq_{j,k,t-l}} + \sum_{j=2}^{6}\in_j \widehat{ii_{k,t-2}} \\ & + \sum_{j=2}^{6}\theta_j \widehat{va_{k,t-2}} + \sum_{j=2}^{6} D_j + year_{FE} + sector_{FE} + u_{k,t}\end{aligned} \quad (4)$$

Here, D_j represents the dummy variable for sector *j*. We include dummy variables for all the sectors except agriculture to avoid the dummy variable trap. Also, we interact the other explanatory variables with these dummy variables.

The primary data source used for the panel data analysis is the India KLEMS database, version 2020. This provides the estimated TFP growth rates for the economy and for 27 individual industries which have been aggregated to the above-mentioned seven sectors. Data on some of the explanatory used for the analysis are drawn from the India KLEMS database. However, for many of the other explanatory variables used for the analysis, other data sources have been used, such as the Penn World Tables, India KLEMS, OCED, DGIS, WIPO, and CEIC. Due to potential endogeneity issues in the estimation of the determinants of TFP growth, an Instrumental Variable approach has been applied which may provide consistent and unbiased estimates. Further details of the data are provided later in the paper.

For the panel-data analysis, we have aggregated 27 industries into seven broad sectors. These sectors are: 1) agriculture & allied activities, 2) high-tech manufacturing, 3) medium to low-tech manufacturing, 4) infrastructure industries that include mining, construction an electricity, gas and water supply, 5) financial services, 6) market services, and 7) non-market services that include public administration, defence, health and education related services (see Table A7 in **Appendix** for the mapping). For these seven sectors, the data span the period 1991 to 2018.

For the sectoral TFP growth rates, we take the average of the industry-wise TFP growth rates from the India KLEMS database, using the GVA shares of those industries within the sectors as weights (see Table A7 for the industry-sector mappings). In the case of agriculture, we did not have to carry out these aggregations as this sector comprises only a single KLEMS industry. Capital deepening is measured by the annual growth rate in the value of the stock of fixed capital in the sector. The capital stock is the stock of fixed capital assets at the end of the year for an industry. The fixed capital includes capital assets of three types—buildings, machinery, and transport equipment. The values of fixed capital in INR are provided for 27 KLEMS industries in the India KLEMS database. We simply aggregate these industry-level values for fixed capital stocks to arrive at the corresponding sectoral values. We measure the growth rates of these sectoral values over the sample years and use that as an explanatory variable in our empirical exercise. Second, we use growth in labour quality as an important determinant of TFP growth rates at the sectoral levels. In the India KLEMS database, the labour quality index is based on the growth rate in workers in five broad educational categories, viz. below primary, primary, middle, secondary and higher secondary, and above higher secondary, weighted by their share in the total emoluments of the industry, less the growth rate in the number of workers. This is computed for each of the 27 industries. Data on the average daily wage earnings are used for computing the labour quality index. In order to arrive at the sectoral index, we average industry-wise indices within a sector as defined, using the share of an industry in the total employment for the sector as weights. The industry-wise information on total employment measured as the number of workers is available in the India KLEMS database. Similarly, India KLEMS data also provide capital composition indices for 27 industries, that are based on the average rental earnings by three types of capital, viz., machinery, transport equipment and buildings, weighted by their shares in the aggregate value of fixed capital stock within a KLEMS-industry. The growth rate in capital services is first computed and then the growth rate in capital stock is subtracted to derive the growth rate in capital composition. In addition, the India KLEMS database provides estimates of GVA and the total values of intermediate inputs used by an industry, both reported in INR. Intermediate inputs in an industry comprise the value of energy used in the activities, the cost of intermediate raw materials, and the cost of services availed from any other activity. Like the capital stock, we simply aggregate GVA and values of intermediate inputs at the sectoral levels.

To capture the productivity growth gains that accumulate from the linkages among industries, we estimated the weighted sum of industrial productivity growth[6]. First, we have aggregated input output transaction table (IOTT) industries to form 7 board sectors. And a concordance table between the classification used in our study and each Input Output Transaction Table has been prepared for this purpose. Second, intermediate inputs have been categorized into 7 broad categories, such as agriculture, infrastructure, low-tech manufacturing, high-tech manufacturing, market services, financial services and non-market services using a standard NIC product classification. Third, we obtained TFP growth rates for these 7 broad sectors. Finally, we have estimated the weighted sum of these 7 sectors' productivity growth for each sector. The weights are based on the proportion of intermediate input acquired from a particular sector.

We have constructed the sector-level exports in INR from the CEIC database which collects data from India's official sources. The disaggregated data on exports were available since 1996 for all the sectors, except the non-marketed services. Therefore, in the models where we use exports as an explanatory variable, we drop non-marketed services. The disaggregated sectoral exports for two services sectors were available from India's balance of payments data that are collected from CEIC database. The data on equipment to total assets ratios are obtained from the published data from India's National Accounts Statistics (NAS) that are also used in the construction of the capital composition index in the India KLEMS database.

Summary statistics for all the variables used in this paper are presented in Table A8(a) and Table A8(b) in **Appendix**.

5. Results

5.1. Estimates Based on Time-Series/All-India Data

The period covered for the analysis of the determinants of TFP (total factor productivity) growth in the Indian economy at the aggregate level is 1982-83[7] (written as 1982) to 2018-19 (2018). The latter analysis is undertaken in two steps: first, only two explanatory variables, namely rainfall, and the growth in GDP of OECD countries are considered, and then in the next stage certain other determinants are included.

[6]According to Jones (2011), an industry may benefit from increased productivity in other industries from which it acquires intermediate inputs. Intermediate goods provide links between industries.

[7]The KLEMS database version 2020 which is used for the analysis presented in the paper provides data from 1980-81 to 2018-19. For the analysis is this section of the paper, the series from 1981-82 onwards is used, i.e. growth rates from 1982-83 onwards are considered. It may be pointed out that the year 1981-82 has been the base of one of the wholesale price index series in India and may thus be considered a normal year. Accordingly, it is appropriate to consider the TFPG series from 1982-83 onwards.

5.1.1. Effect of Rainfall and OECD GDP Growth on TFPG in the Indian Economy

As mentioned above, in this sub-section, an econometric analysis of the determinants of the aggregate economy level TFP growth is done by considering only two explanatory variables: 1) the deviation of rainfall from the long-period average and 2) the growth rate in OECD countries' GDP (at constant prices). For these two explanatory variables, time-series data could be obtained from the entire period for which data on TFPG exists in the India KLEMS database. For this analysis, data for the period 1982-83 to 2018-19 are used. In the second stage, which is presented in the next sub-section, several other explanatory variables are introduced into the analysis including the share of ICT capital stock in total capital stock. Due to certain limitations of data availability, the second part of the analysis is confined to a shorter period, 1995-96 to 2018-19.

A positive effect of rainfall on the aggregate economy level TFP growth on the economy-level TFP growth rates (denoted by TFPG_India) is expected. It should be mentioned here that in the study on the sources of India's economic growth undertaken by Virmani (2004), a positive effect of rainfall was found. Similarly, there are ground to expect that a higher rate of growth in GDP in OECD member countries will have a positive effect on TFP growth in the Indian economy since this will help India attain a faster growth in exports which in turn is expected to have a positive effect on productivity.

Before the analysis of the determinants of TFPG is presented, it would be useful to consider the correlation of TFP growth with deviation in rainfall and the growth rate in GDP of OECD countries. This is depicted in **Figure 5**. The correlation coefficients are shown for various 15-year interlocking periods shown against the terminal year. Thus, the correlation coefficient for the period 1982-83 to 1996-97 is shown against 1996-97. In the graph, the correlation coefficients are shown for various periods with terminal years ranging from 1996-97 to 2018-19.

The correlation coefficient of TFPG with the deviation in rainfall over the previous 15 years was about 0.6 in 1996 and 1997 and remained above 0.4 till 2013. There was a significant downward trend since then. In 2018, the correlation coefficient between TFPG and the deviation in rainfall during the previous 15-year period was only 0.04. The downward trend in the correlation coefficient between TFPG and deviation in rainfall, which is observed in the graph after 2006 may be attributed to the decline in the GDP share of agriculture and allied activities (a sector that is relatively more impacted by the variations in rainfall) and possibly also to the fact that the dependence on hydel power has declined over time (since one may justifiably assume that hydel power generation will be impacted by the extent of rainfall). Also, the change in the industrial structure from agriculture-based industries to metal-based and chemical-based industries in India over time may have made the effect of rainfall on the economy go down progressively. It is also possible that the agriculture sector has now become more resilient to variations in rainfall. Since agriculture impacts the rest of the economy through demand linkage as well as supply linkage as the provider of agriculture-based inputs for industry, greater resilience of agriculture to rainfall variations is likely to make the rest of the economy also less affected by variations in rainfall.

The correlation between TFPG in the Indian economy and the OECD GDP growth rate has been relatively stronger during the 15-year interlocking periods spanning the late 1980s to the early 2000s. For other periods, the correlation coefficient is found to be mostly in the range of 0.2 to 0.3 which is not statistically significant (for $n = 15$).

Between 1982 and 2008, the correlation coefficient between TFP growth and deviation in rainfall is found to be 0.62, and that for the period 2009 to 2018 is found to be only 0.04. For the growth rate in real GDP of OECD countries, the correlation coefficient with TFP growth rate in the Indian economy is 0.46 for the period 1982 to 2008, and lowers at 0.40 for the period 2009 to 2018.

While variations in the growth rate in real GDP of OECD countries are expected to impact TFP growth in the Indian economy, it is unlikely to be impacted by the rate of TFP growth in the Indian economy. Thus, there is justification for taking the growth rate in GDP of OECD member countries as a variable explaining TFP growth in the Indian economy. The main route through which the effect is expected to occur is exports. However, fast growth in the GDP of OECD member countries could impact TFP growth in the Indian economy via other channels such as business confidence and investment flows.

From **Figure 5**, it may be seen that the correlation between growth in GDP of OECD member countries and TFP growth in the Indian economy was relatively higher in the 1980s and 1990s than that during the second half of the 2000s and 2010s. This is perhaps a reflection of the changes in the destination-wise structure of India's exports. The share of the USA and the European countries in India's exports was higher in the 1980s than in the 2010s.

The results of the ARDL model are presented in **Table 1**. The results show

Table 1. Estimates of the ARDL model explaining TFPG at the economy level: long-run coefficients. Dependent variable: Year-on-year growth in aggregate TFP.

Explanatory variables	Coefficients
Deviation of rainfall from the long-period average (percent)	0.083*** (4.05)
Year-on-year growth in GDP of OECD countries	0.509*** (3.04)
Adjustment coefficient	−1.66*** (−7.31)
R^2 of the error correction model	0.81
Peseran et al. (2001) bounds test	F = 20.6; t = −7.3
No. of observations	23 (1986-2008)

Source: Authors' computations. Note: ARDL structure (2, 0, 0) is used. The optimal lag lengths are determined by Bayesian information criteria. t-statistics are in the parentheses. *** indicates statistical significance of the coefficients at 1 percent.

that if the rainfall in a year is above the long period average, this has a positive effect on the growth rate in TFP at the aggregate economy level. If the rainfall is 10 percent higher than the long period average, it will enhance the rate of TFP growth by 0.8 percentage points. As regards the growth rate in GDP in OECD countries, it has a positive effect on the TFP growth rate of the Indian economy. From the results, it may be inferred that a one percentage point hike in the growth rate of GDP of OECD countries raises the rate of TFP growth of the Indian economy by about 0.5 percentage points.

Further, the results of Peseran et al.'s (2001) bounds test indicate that a level relationship exists, i.e. there is the presence of co-integration. The value of the adjustment coefficient at (−)1.66 may be interpreted as showing oscillating convergence.

It should be emphasized that the results presented in **Table 1** reflect the nature of the relationship that prevailed during 1982 to 2008. In the subsequent period, there has been a change in the relationship (as indicated by the graphs on the correlation coefficient) and the impact of changes in rainfall and the growth rate in OECD GDP on the rate of TFPG in the Indian economy has probably gone down. This is the reason why the rainfall-related variable has been dropped in the next part of the econometric analysis.

Figure 6 compares the actual TFP growth rate of the Indian economy compared with that is predicted by the above ARDL model. Although the estimation of the model has been done using data up to 2008, the predicted TFPG has been derived for the subsequent period also. The predicted TFPG shows a good deal of similarity with the actual TFPG, within the sample period and for several years beyond the sample period. However, for the period 2014 to 2018, the model predicts a negative growth rate in TFP in the Indian economy, whereas, in reality,

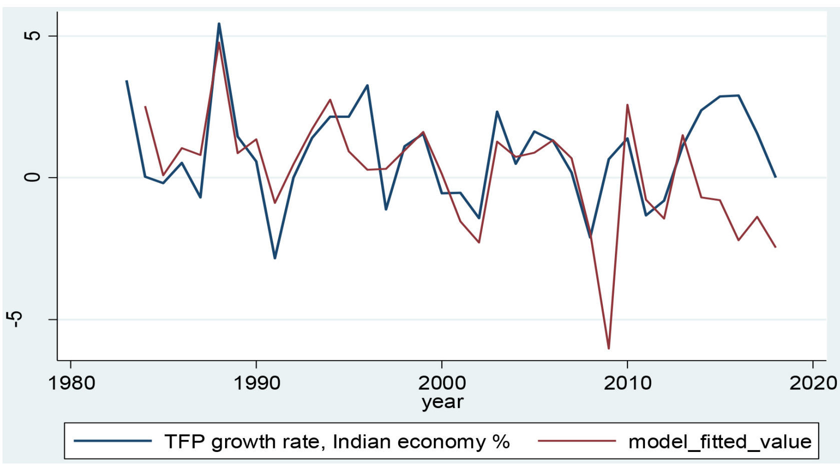

Figure 6. TFP growth rate of the Indian economy and the ARDL model fitted value. Source: Authors' computations. Note: The model has been fitted using data up to 2008-09, which has been used for predicting TFPG for the period up to 2008-09 and beyond. Since rainfall data and OCED GDP data are available for 2009-10 to 2018-19, the model predicts TFPG for those years.

there has been no fall in TFP in this period; rather, there was a positive TFP growth of 1.5 percent or higher between 2014 and 2017. In 2018, TFP growth was marginal, but not negative. This difference between the model predicated TFP growth and actual TFP growth is explained by the fact that the model makes use of certain parameters linking rainfall to TFPG which though valid for the sample period did not remain valid for the later period (as is evident in Figure 6). Also, there are possibly other factors that have impacted the rate of TFP growth of the Indian economy in recent years apart from rainfall and the GDP growth rate in OECD countries.

Figure 7 plots the unexplained portion of the TFP growth from this model. This plot suggests the growth in TFP that did not result from domestic shocks and external factors that result in fluctutaions in output but are not directly linked with technological progress or productivity growth. The residual plotted in Figure 7 broadly suggest the TFP growth which could be more "structural" in nature, as that excludes components from two largest shocks to the output or TFP. The 5 years centred moving averaged (5Y CMA) line broadly suggests the underlying trend of the TFP growth rate, after accounting for what can be explained by some "exogenous" factors. It can be seen in Figure 7 that the residual TFP growth (5Y CMA) was broadly negative during 1980s and the first few years in 1990s. It improved during the next decade, but remained negative. This TFP growth entered the positive territory in the last decade, which suggests that the aggregate TFP growth might have increasingly been driven by factors other than those that are exogenous to India. Therefore, the persistent pattern in the TFP growth unexplained by rainfall deviation and the GDP growth in OECD countries suggests that there might be increasing scopes for policy interventions and creating enablers which could potentially drive TFP growth in India.

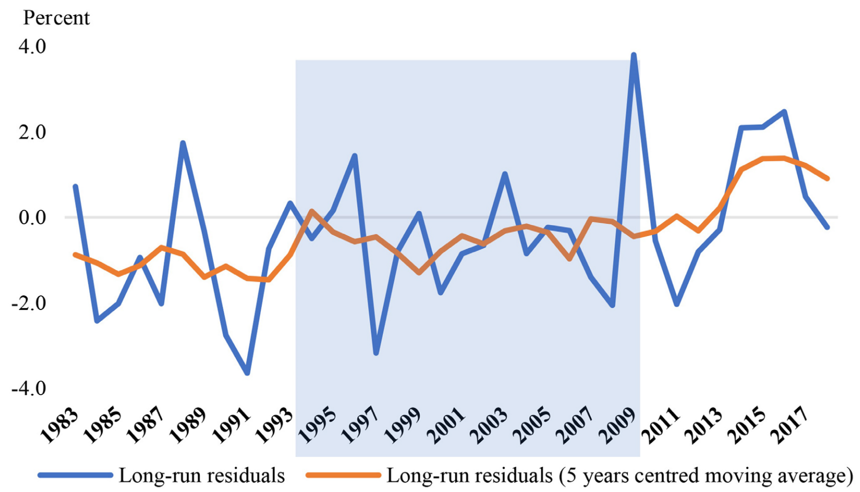

Figure 7. Residuals from the ARDL model (long-run specification). Source: Authors' computations. Note: The model has been fitted using data up to 2008-09, which has been used for predicting TFPG for the period up to 2008-09 and beyond. Since rainfall data and OCED GDP data are available for 2009-10 to 2018-19, the model predicts TFPG for those years.

5.1.2. Analysis with Additional Determinants for Aggregate All-India TFP Growth

In the analysis above, the effects of deviation in rainfall from the long-term average and the growth rate in GDP of OECD countries on the TFP growth rate in the Indian economy was studied using data up to 2008. In the next step, several new explanatory variables are considered for explaining the TFP growth rate of the Indian economy. Since data on some of these variables are not readily available for the 1980s, the period of the analysis is different from that in the previous sub-section; it is mostly from 1995 to 2018 but in some cases, data for 1993 to 2018 or a longer period has been used.

The results of the estimation of the ARDL model are presented in Table 2. It has not been possible to include all six explanatory variables in one model. Therefore, different combinations of variables have been used. Some of the

Table 2. Estimates of the ARDL model explaining TFPG at the economy level: long-run coefficients.

Explanatory variables	Dependent variable: year-on-year growth in TFP								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Year-on-year growth in trade-weighted TFP for India's 34 trade-partners	0.143 (0.58)		0.154 (0.64)				0.130 (0.47)	0.933** (2.27)	
Annual rate of change in the share of ICT capital assets in the stock of all fixed assets	4.30* (1.97)		5.91*** (3.43)		5.36** (2.79)	6.09*** (5.69)			
TFP growth rate in infrastructure industries		0.26*** (3.10)					0.27** (2.79)	0.09 (0.88)	
Net cumulative public investment in infrastructure normalized by GDP	0.36** (2.46)	0.24 (1.34)	0.41** (2.53)		0.27 (1.43)	0.20* (2.03)		0.45*** (3.08)	0.26 (1.01)
Ratio of cumulative FDI in the past five years to GDP		0.56*** (3.39)	0.30 (1.85)*	−0.08 (−0.30)	0.34* (1.87)		0.18* (1.82)		0.58** (2.43)
Growth rate in GDP of OECD countries				0.43* (1.79)					
Trend	Included			Included				Included	
ARDL lag structure	(1, 0, 0, 1)	(1, 1, 1, 0)	(1, 0, 1, 0, 0)	(1, 1, 0)	(1, 0, 1, 0)	(3, 1, 0)	(1, 0, 0, 0)	(1, 3, 1, 2)	(1, 1, 0)
Adjustment coefficient	−1.09*** (6.20)	−1.12*** (−6.29)	−1.10 (−6.27)	−0.96*** (−4.18)	−0.99*** (−6.40)	−1.67*** (−5.20)	−0.97*** (−5.76)	−1.12*** (−5.30)	−0.82*** (−5.20)
R^2 of error correction model	0.76	0.79	0.77	0.51	0.78	0.80	0.58	0.85	0.70
Peseran et al. (2001) bounds test	F = 12.1; t = (−)6.2	F = 13.0; t = (−)6.3	F = 10.2; t = (−)6.3	F = 6.4 t = (−)4.2	F = 12.6; t = (−)6.4	F = 11.6; t = (−)5.2	F = 8.7; t = (−)5.8	F = 10.0; t = (−)5.3	F = 11.5; t = (−)5.2
Inference about the existence of level relationship: Null hypothesis of no level relationship is	rejected at a 1% level	rejected at a 1% level	rejected at a 1% level	rejected at a 10% level	rejected at a 1% level	rejected at a 1% level	rejected at a 1% level	rejected at a 1% level	rejected at a 1% level
No. of observations (Sample period)	26 (1993-2018)	24 (1995-2018)	26 (1993-2018)	29 (1990-2018)	24 (1995-2018)	24 (1995-2018)	30 (1989-2018)	26 (1993-2018)	24 (1995-2018)

Note: t-values in parentheses. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. The optimal lag length has been determined on the basis of Bayesian information criteria. For Model (8), this has been fixed on the basis of trial and error. Source: Authors' computations.

models have been estimated using data for 1995-2008. In certain other cases, data for a longer period has been used. The results indicate that investment in infrastructure and the efficiency with which the infrastructure industries are functioning (as reflected in the rate of TFP growth of infrastructure industries) have a significant positive impact on TFP growth in the Indian economy. The inflow of FDI is found to have a significant positive effect, possibly with some lag. A strong positive effect of investment in ICT on TFP growth in the Indian economy is found. In all these cases, the coefficient is found to be positive and statistically significant in one or more regressions.

The results in respect of the growth rate in GDP in OECD countries and the rate of TFP growth achieved in the countries which are India's important trade partners are not strong. In one regression, the coefficient of the growth rate in GDP in OECD countries is found to be positive and statistically significant. This finding along with the model estimate presented in **Table 1** may be treated as indicating that faster growth in GDP in OECD countries tends to raise the growth rate in TFP in the Indian economy. For the variable representing TFP growth among India's trade partners, the coefficient is found to be positive in several regressions. In one regression, the coefficient is both positive and statistically significant. Thus, there is an indication that TFP growth in leading trade partners of India has an impact on TFP growth in the Indian economy. The results of Peseran et al.'s (2001) bounds test show that the null hypothesis of there being no level relationship is rejected at a one percent level in all regressions except one where the null hypothesis is rejected at a 10 percent level. Thus, there is an indication of the presence of co-integration. The adjustment coefficient is negative and statistically significant. In several cases, it is below one in absolute value. In some cases, it exceeds one in absolute value but does not exceed 2. Thus, it may be inferred that there is convergence.

5.2. Estimates Based on Panel/Sector-Wise Data

Estimates from the Pooled Group Mean estimation following Peseran et al. (1999) for panel dataset with mixed order of integration suggest that higher TFP in input-producing sectors are associated with higher TFP growth in the seven sectors in our paper (**Table 3**). For instance, higher aggregate growth in TFP in the sectors from where the manufacturing activities gather their input results in higher TFP growth in the manufacturing sector. This reflects that an efficient supply chain mechanism boosts productivity growth. Second, a sector's higher international exposure measured by the value of exports is associated with higher TFP growth in the sector. These two coefficients are robust in different specifications. The coefficient of equipment ratio, however, was found to be negative and significant. When we use the growths instead, the coefficients turn out to be statistically insignificant. However, this requires some research in the future. The error correction terms suggest that the variables might constitute an equilibrium system in the long-run (**Table 3**).

Table 3. Estimates of panel ARDL (pooled group mean): long-run coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: Δlog(TFP)					
TFP in input producing sector	0.76*** (0.15)	0.68*** (0.14)	0.80** (0.33)	1.22*** (0.29)	1.20*** (0.29)	1.42*** (0.31)
Exports (INR)	0.058*** (0.0059)	0.064*** (0.0047)	0.099*** (0.014)	0.063*** (0.0091)	0.063*** (0.0089)	0.066*** (0.0094)
Equipment-structure ratio	−0.12*** (0.032)	−0.16*** (0.031)				
Δ(equipment-structure ratio)			−1.31** (0.51)			
Δ(Equipment-structure ratio)-1 year lag				0.055 (0.22)	0.043 (0.22)	−0.16 (0.23)
Adjustment coefficient	−0.25* (0.14)	−0.33* (0.18)	−0.20** (0.085)	−0.23** (0.100)	−0.23** (0.10)	−0.21** (0.094)
Constant	−0.17 (0.11)	−0.25* (0.15)	−0.25** (0.10)	−0.20** (0.10)	−0.20* (0.10)	−0.20* (0.10)
N	126	120	120	120	120	120
Log likelihood	272.66	267.06	267.95	262.45	263.54	273.09
Sample period	1996-2018					

Note: TFP: Total factor productivity index (FY1991-92 = 1). Indices for TFP and the values of exports are expressed in natural logarithm. Standard errors in parentheses, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Further, estimates based on 2SLS IV regression suggest that contemporaneous growth in physical capital and labour quality are associated with increased growth in TFP. Capital composition, however, has statistically insignificant coefficients (Table 4). The interpretation of the coefficients of capital deepening and labour quality are relatively straightforward. Higher investment in fixed capital which also includes machineries and transport equipments can potentially make a business more productive by increasing every worker's contribution towards the output. The coefficient of capital composition, however, requires some thought. Like labour, capital composition index indicates the average rental price across three types of capital; viz. buildings, machineries and transport equipment. Now, following a theory of competitive market, higher rental price of capital would mean that the capital stock available with sector is more productive. In this case, like the labour quality index, we should expect a positive sign for this variable. However, we obtain a negative and statistically insignificant coefficient for thois variable. In order to look more closely, in our next 2SLS IV estimate, we introduce sector dummy interactions with these three endogenous variables (Table 5). Our estimates regarding capital composition suggest that the coefficient is negative and statistically significant for agriculture and allied activities, used as the reference sector in this regression. The coefficient values for the interactions

Table 4. Estimates from 2SLS-IV: all sectors.

	(1)	(2)
	Dependent variable: Δ(TFP)	
Δ(TFP)-1year lag	0.07	0.11
	(0.08)	(0.07)
Δ(capital stock)	**5.82****	**6.13****
	(2.06)	**(2.08)**
Δ(labour quality)	9.71	**51.11****
	(13.92)	**(18.49)**
Δ(capital composition)	−14.40	−11.17
	(8.91)	(11.31)
Δ(intermediate inputs)-2 years lag	0.14*	0.15*
	(0.07)	(0.07)
Δ(GVA)-2 years lag	−0.09	−0.10
	(0.11)	(0.10)
Δ(capital stock)-1 year lag		−1.41
		(1.06)
Δ(labour quality)-1 year lag		−46.74**
		(12.76)
Δ(capital composition)-1 year lag		−5.35
		(3.87)
Constant	0.03	0.00
	(0.02)	(0.03)
N	161	154
R^2 overall	0.28	0.31
Sample period	1991-2018	

Note: TFP: total factor productivity index (FY1991-92 = 1). All variables are expressed in natural logarithm. Models include dummies for individual years and sector fixed-effects. Standard errors in parentheses, $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5. Estimates from 2SLS-IV: sector dummy interactions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Agriculture and allied activities	Infrastructure industries	Low technology manufacturing	Mid-high technology manufacturing	Market services	Financial services	Non-market services
	Dependent Variable: Δ(TFP)						
Δ(capital stock)	1.61	−0.08	8.86***	6.75**	11.43***	1.61	2.20
	(1.22)	(3.75)	(0.98)	(2.27)	(2.96)	(2.14)	(2.47)
Δ(labour quality)	52.76***	−92.52	−33.26	−50.00	−235.03	−70.88	−38.75

Continued

	(9.53)	(61.20)	(24.94)	(86.04)	(126.43)	(43.40)	(64.14)
Δ(capital composition)	−99.07***	72.25**	89.06**	78.26**	121.88***	112.99***	76.74***
	(25.12)	(20.81)	(27.23)	(22.38)	(32.73)	(28.07)	(19.45)

Model uses 161 observations in all and has an overall R^2 of 0.14. Notes: Model controls for 1 - 3 years of lags on TFP, second lags of intermediate input growth and GVA growth. Sample period is between 1991 and 2018. All variables are in their natural logarithm. Model includes a constant, dummies for individual years and sector fixed-effects. Standard errors in parentheses, $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

with other sectors are positive, indicating that this effect might be gradually increasing for other sectors. The aggregate effect, however, remains much smaller for infrastructure industries that include labour-intensive sectors like mining and construction; and non-market services. The aggregate coefficients are highest for the market services and financial services sectors. The exact channel of how these differences occur, however, could be taken as future research. Lastly, our estimates in Table 5 suggest that fixed capital growth is associated with higher TFP growth in manufacturing and in market services. Labour quality continues to hold a positive effect on all sectors.

6. Conclusion

This paper contributes to the literature by investigating the impact of capital deepening, growth in labour quality, growth in the unit cost of capital, input use intensity, participation in the global value chain and international trade, ICT, R&D expenditure, and FDI on the total factor productivity (TFP) growth in India. For this purpose, we use India KLEMS data that provide us with comparable estimates of TFP and other variables for the entire economy. We classify the 27 activities available in India KLEMS into seven broad sectors—agriculture, infrastructure industries, manufacturing, market services excluding financial services, non-market services and financial services. The empirical methodology is divided into two parts. First, we use the time series (ARDL) model to capture the maximum set of determinants of TFP based on the availability of sufficient data at the aggregate level, but it cannot be used in a panel set-up since they are not available at the industry level. Secondly, we use a panel data model to control for some unobserved factors using the period and industry-specific dummy variables.

From the time series (ARDL) model, we observe that rainfall above the long period average (LPA) has a positive effect on the TFP at the aggregate economy level. It shows that a 10 percent increase in rainfall above the LPA will lead to an increase in TFP growth by 0.8 percentage points. Further, the growth rate in GDP in OECD countries also has a positive effect on the TFP growth rate of the Indian economy. It also shows that a one percentage point increase hike in the growth rate of GDO of OECD countries raises the rate of TFP growth of the Indian economy by about 0.5 percentage points. Further, the results of Peseran et al.'s (2001) test indicate that there is a presence of cointegration among these three variables, which shows oscillating convergence. In this exercise, apart from these two variables, several new variables, based on either theory or literature, have been considered for explaining the TFP growth rate of the Indian economy. It is observed that investment in infrastructure and the efficiency with which the infrastructure industries are functioning have a significant positive impact on TFP growth in the Indian economy. The inflow of FDI is also found to have a significant positive effect, possibly with some lag. A strong positive effect of investment in ICT on TFP growth in the Indian economy is also found. In all these cases, the coefficient is found to be positive and statistically significant in one or more regressions.

From the panel data model, we observed that higher TFP growth in input-producing sectors is generally associated with higher TFP growth in the seven sectors in our paper. For instance, manufacturing sectors that use inputs with high TFP growth witness a higher aggregate growth rate in TFP. This demonstrates the role of an efficient supply chain mechanism in productivity growth. It is also observed that higher international exposure measured by the value of exports by a sector is associated with higher TFP growth in the sector. This corroborates our findings in time series analysis, where it was observed that higher GDP growth in OECD countries leads to higher TFP growth in India. Further, estimates based on 2SLS IV regression suggest that contemporaneous growth in physical capital is associated with higher growth in TFP in manufacturing and market services. Labour quality is associated with increased growth in TFP in all sectors. Higher rental price of capital generally hurts TFP growth in more labour-intensive sectors like agriculture, mining, construction and non-market services. In market services and financial services, the higher rental price of capital is associated with increased TFP growth. A higher rental cost of capital driven by higher demand for capital, therefore, can induce higher TFP growth, only if it is accompanied by appropriate research and development (R&D) activities that effectively bring down the capital's cost.

Our findings from the study yield the following policy implications. As capital deepening in the form of growth in fixed capital stock generally improves TFP growth, moving resources away from labour-intensive technology and increased automation could probably pave the way for sustained growth in TFP. Improvement in the educational status of the labour force has also been found to be a significant factor behind TFP growth across all sectors. However, retaining high-skilled workers, especially in the manufacturing sector, would be a priority for sustaining the improvements in TFP through labour quality growth. Thus, investments in education to raise labour capabilities are crucial for better absorbing foreign technology, especially for exploiting benefits from FDI. The unit cost of capital, if driven solely by the exogenous shift in the investment demand conditions, generally deteriorates TFP growth. Hence, greater focus should be on innovation that improves the return from the capital, so that the rental price/interest rate is least affected, or even reduced, when investment demand rises. Since our study finds that there is a direct impact of rainfall above the LPA on the TFP, government should give more emphasis on green initiatives, which is one of the most important issues during the recent period across the globe. Although it is true that this is a long-drawn process, there is a need to stop the climate change, which may affect the seasonal rainfall and hence the overall TFP of our country. Finally, since our study finds that higher growth in OECD countries leads to higher TFP growth in India due to their strong trade relation with India, government should provide more incentives to facilitate terms of trade with the OECD countries.

To sum up, the results obtained in our study find structural variables like rainfall, higher FDI, and physical capital are positively associated with the total factor productivity growth of the Indian economy. Our results suggest that the factors which affect productivity globally are also important drives of productivity for India. One important aspect which remains to be explored here is the role of global value chains and digitalization in driving productivity growth. GVCs affect productivity growth through access to a larger variety of imported inputs and technical know-how. Further studies by OECD have shown that digitalization and new technologies like artificial intelligence, and cloud computing are transforming economies and improving the productivity of firms. Thus, possible future research agenda could be to analyse if GVC participation and digitalisation affect TFP growth at a macro level for India.

Statements and Declarations

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Table A1. Unit root tests, augmented dickey-fuller test and Phillips-Perron test, 1982-2008.

Variables	Augmented Dickey-Fuller test		Phillips-Perron test	
	Levels	First difference	Levels	First difference
TFP growth rate	−4.99	−8.12	−4.98	−8.46
Rainfall deviation from long period average	−5.11	−10.85	−5.14	−11.34
Growth rate in GDP of OECD countries	−3.62	−5.06	−3.76	−5.16

Note: For the augmented Dickey-Fuller test, the critical value at a 1% level is 3.7, and at a 5% level, it is 3.0. For the Phillips-Perron test, the critical values at 1% and 5% levels are 3.75 and 3.00 respectively. In the case of the growth rate in GDP of OECD countries, the critical value at a 1% level is crossed by the statistic of the Phillips-Perron test, whereas the statistic of the Dickey-Fuller test falls marginally short of the 1% level critical value. Source: Authors' computations.

Table A2. Unit root test, augmented dickey-fuller test, and Phillips-Perron test, 1995-2018, additional variables used for modelling.

Variable	Augmented Dickey-Fuller test		Phillips-Perron test	
	Levels	1st difference	Levels	1st difference
Change in the share of ICT assets in total capital stock	−0.06	−5.24	−0.12	−5.21
Ratio of FDI (cumulative over five years) to GDP	−2.03	−6.68	−2.08	−6.57
Cumulative public investment in infrastructure divided by GDP	−3.754	−3.02 −4.43*	−3.62	−2.90 −4.41*
TFP growth rate in infrastructure industries	−2.53	−5.62	−2.60	−5.66
TFP growth rate among 34 trading partner countries (weighted average)	−4.19	−6.97	−4.16	−8.75
Growth rate in GDP of OECD countries	−3.61	−6.60	−3.58	−7.33

Note: The critical value at a 1% level is −3.75 and at a 5% level, it is −3.00 for the augmented Dickey-Fuller test and the Phillips-Perron test. After allowing for trend, the critical values are −4.38 at the 1% level and −3.60 at the 5% level. *Allowing for trend. Source: Authors' computations.

Table A3. Unit root tests for TFP growth rate: 1995-2018.

Variable	Augmented Dickey-Fuller test		Phillips-Perron test	
	Level	1st difference	Level	1st difference
TFP growth rate	−3.73	−6.5	−3.68	−7.0
TFP growth rate, allowing for trend	−3.66	−6.3	−3.60	−6.9

Note: The critical values are the same as in the note in Table 3. It is −3.75 at a 1% level of statistical significance. Source: Authors' computations.

Table A4. Hausman specification test.

	(b)	(B)	(b − B)	sqrt(diag(V_b − V_B))
	FE	RE	Difference	S.E.
TFP-1 year lag	0.105	0.125	−0.020	0.011
Equipment/Total assets	−0.006	−0.015	0.009	0.042
TFP in input producing sector	0.073	0.114	−0.041	0.066
Exports	0.003	0.001	0.002	0.004

Note: b = consistent under Ho and Ha; B = inconsistent under Ha, efficient under Ho; Test: chi2(4) = (b − B)'[(V_b − V_B)^(−1)](b − B) = 3.75; Prob. > chi2 = 0.4404. Note: Test fails to reject the hypothesis of no difference in the coefficients. This suggests that variables might not be endogenous.

Table A5. Hausman specification test.

	(b)	(B)	(b − B)	sqrt(diag(V_b − V_B))
	FE	RE	Difference	S.E.
TFP-1 year lag	0.070	0.066	0.004	0.005
Equipment/Total assets	0.017	−0.005	0.021	0.016
TFP in input producing sector	0.011	−0.049	0.060	0.020
Exports	0.000	0.002	−0.002	0.001
Δ(capital stock)	−0.666	−0.755	0.089	0.026
Δ(labour quality)	−1.078	−1.573	0.495	0.303
Δ(capital composition)	−0.451	−0.468	0.017	0.072
Δ(intermediate inputs)	0.013	−0.006	0.019	0.005
Δ(GVA)	1.003	0.963	0.040	0.008

Note: b = consistent under Ho and Ha; B = inconsistent under Ha, efficient under Ho; Test: Ho: difference in coefficients not systematic; chi2(5) = (b − B)'[(V_b − V_B)^(−1)](b − B) = 45.12; Prob. > chi2 =0.000; (V_b − V_B is not positive definite). Note: Test rejects the hypothesis of no difference in the coefficients. This suggests that additional variables might be endogenous.

Table A6. Validity of instruments for endogenous variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Dependent variable: Δ(capital stock)			Dependent variable: Δ(labour quality index)			Dependent variable: Δ(capital composition index)		
Δ(capital stock)-1 year lag	0.69***	0.69***	0.68***				0.03*		
	(0.05)	(0.05)	(0.05)				(0.01)		
Δ(capital stock)-2 year lag								−0.00	
								(0.01)	
Δ(capital stock)-3 year lag									0.01
									(0.03)

Continued

Δ(capital composition index)-1 year lag							0.35**	0.36**	0.34**
							(0.11)	(0.11)	(0.10)
Δ(labour quality index)-1 year lag				0.77***	0.82***	0.80***			
				(0.08)	(0.13)	(0.12)			
Δ(labour quality index)-2 years lag					−0.07	−0.06			
					(0.09)	(0.10)			
Δ(intermediate inputs)	0.05*	0.05*	0.05*						
	(0.02)	(0.02)	(0.02)						
Δ(intermediate inputs)-1 year lag		0.01	0.02						
		(0.03)	(0.03)						
Δ(intermediate inputs)-2 years lag			−0.01						
			(0.02)						
Δ(labour-capital ratio)-1 year lag				−0.10	−0.09	−0.03			
				(0.28)	(0.29)	(0.27)			
Δ(labour-capital ratio)-2 years lag				0.19	0.20	0.12			
				(0.31)	(0.32)	(0.32)			
Δ(labour-capital ratio)-3 years lag				0.01	−0.00	0.03			
				(0.06)	(0.07)	(0.09)			
Δ(labour-capital ratio)-4 years lag				−0.28*	−0.27*	−0.18*			
				(0.12)	(0.14)	(0.09)			
Δ(labour-capital ratio)-5 years lag						−0.09			
						(0.16)			
Constant	0.01*	0.01*	0.02*	0.00*	0.00**	0.00	−0.00	−0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	182	182	175	161	161	154	182	175	168
R^2 overall	0.65	0.65	0.65	0.76	0.76	0.74	0.33	0.33	0.30

Note: All variables in natural logarithms. Regressions include year and sector specific dummy variables. Standard errors in parentheses, $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A7. Mapping of sectors used in the paper with India KLEMS.

SL no.	KLEMS industry description	Sector classification in this paper
1	Agriculture, hunting, forestry and fishing	Agriculture and allied
2	Mining and quarrying	Infrastructure Industries
3	Food products, beverages and tobacco	Agriculture and allied
4	Textiles, textile products, leather and footwear	Low-technology manufacturing
5	Wood and products of wood	Low-technology manufacturing
6	Pulp, paper, paper products, printing and publishing	Low-technology manufacturing

Continued

7	Coke, refined petroleum products and nuclear fuel	Medium to high-technology manufacturing
8	Chemicals and chemical products	Medium to high-technology manufacturing
9	Rubber and plastic products	Low-technology manufacturing
10	Other non-metallic mineral products	Medium to high-technology manufacturing
11	Basic metals and fabricated metal products	Medium to high-technology manufacturing
12	Machinery, nec.	Medium to high-technology manufacturing
13	Electrical and optical equipment	Medium to high-technology manufacturing
14	Transport equipment	Medium to high-technology manufacturing
15	Manufacturing, nec., recycling	Low-technology manufacturing
16	Electricity, gas and water supply	Infrastructure industries
17	Construction	Infrastructure industries
18	Trade	Market services
19	Hotels and restaurants	Market services
20	Transport and storage	Market services
21	Post and telecommunication	Market services
22	Financial services	Financial services
23	Business service	Market services
24	Public administration and defense; compulsory social security	Non-market services
25	Education	Non-market services
26	Health and social work	Non-market services
27	Other services	Market services

Table A8. (a) Summary statistics of variables used in aggregate analysis (time series estimation); (b) Summary statistics of the variables used panel estimation average (standard deviation) (number of observations).

(a)

Variable	Period	Mean	Standard deviation	Minimum	Maximum
TFP growth rate	1982-2018	0.0079	0.0171	−0.0284	0.0543
Rainfall deviation (%)[#]	1982-2018	2.79	8.54	−22.15	18.41
Growth rate in OECD GDP (%)[#]	1982-2018	2.45	1.43	−3.33	4.71
Year-on-year growth in trade-weighted TFP for India's 34 trade-partners	1982-2018	0.0037	0.0109	−0.0214	0.0314
Annual rate of change in the share of ICT capital assets in the stock of all fixed assets	1991-2018	0.0013	0.0013	−0.0003	0.0049
TFP growth rate in infrastructure industries	1982-2018	−0.0084	0.0359	−0.1056	0.0509
Net cumulative public investment in infrastructure normalized by GDP (%)[#]	1982-2018	30.78	2.23	27.53	35.30
Ratio of cumulative FDI in the past five years to GDP (%)[#]	1988-2018	5.80	3.28	0.079	9.94

[#]These variables are expressed as a fraction rather than in percentage for the purpose of estimating the ARDL model.

(b)

Sector	TFP growth	Labour quality growth	Capital composition growth	Equipment-structure ratio	Input-linked TFP growth	Trade growth
Agriculture and allied activities	1.2 (3.7) [28]	0.3 (0.1) [28]	0.6 (0.3) [28]	9.3 (5.2) [28]	−2.5 (3.5) [28]	11.7 (10.6) [22]
Low-tech manufacturing	1.5 (8.1) [28]	0.6 (0.2) [28]	0.1 (0.9) [28]	40.9 (6.6) [28]	4.3 (4.2) [28]	12.8 (10.3) [22]
Mid to high tech manufacturing	−0.5 (6.1) [28]	0.8 (0.4) [28]	0.2 (0.5) [28]	154.0 (21.8) [28]	4.2 (4.6) [28]	14.9 (10.7) [22]
Infrastructure industries	−0.3 (2.9) [28]	0.5 (0.2) [28]	0.1 (0.6) [28]	99.9 (14.4) [28]	−1.2 (4.1) [28]	15.9 (22.5) [22]
Market services	0.3 (2.0) [28]	0.5 (0.3) [28]	0.7 (0.5) [28]	12.4 (6.8) [28]	0.8 (5.6) [28]	17.4 (11.5) [22]
Non-market services	3.4 (3.6) [28]	0.5 (0.3) [28]	0.3 (0.7) [28]	24.8 (2.0) [28]	1.0 (4.7) [28]	
Financial services	1.7 (4.3) [28]	0.3 (0.4) [28]	0.9 (1.0) [28]	28.0 (9.6) [28]	5.0 (3.6) [28]	19.2 (32.3) [22]
Sample	*1991-2018*	*1991-2018*	*1991-2018*	*1991-2018*	*1991-2018*	*1997-2018*