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# Decomposition of climate-induced productivity growth in Indian agriculture

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## Abstract

This paper adopts a stochastic frontier approach to investigate the trend and determinants of total factor productivity (TFP) growth in the agriculture sector of India, using extensive district-level data. The assessment of the production frontier highlights the efficiency aspect of Indian agriculture and contributes to an analysis of those factors that might be directly engaged in the production process. After controlling for the district-specific climatic effect in the production of eighteen major crops, TFP growth is deconstructed into technical progress, technical efficiency change and scale effects. Four weather parameters, average temperature, rainfall, evapotranspiration and windspeed, are defined as exogenous determinants of the technical inefficiency term to analyze the influence of changing climate. Based on the true fixed effect model and maximum likelihood method, the estimated TFP growth averaged 0.688% per year between 1990 and 2015. The relative performance of Indian states apparently differs according to estimated productivity scores. The findings show that changes in technical efficiency account for most TFP growth, whereas differences in scale components account for annual and cross-state productivity growth disparities. The study suggests that region-specific policies are required to enhance agricultural productivity and add to the understanding of the arguments over TFP growth in Indian agriculture.



*Keywords*: Stochastic frontier analysis; Total factor productivity decomposition; True fixed effect model; Agricultural productivity growth; India

# 1 Introduction

Climate change has its most significant influence in developing countries. Compared to other sectors, agriculture is most affected by changing climate, as it has a direct biophysical effect on crop production. Climate extremes are projected to intensify in the future and, because of the economic importance of climate-sensitive sectors, developing low-income countries are expected to suffer the most from the detrimental effects of climate change [1]. In middle-income countries like India, agriculture has long been an essential source of poverty reduction and continues to be a reasonably large sector in terms of livelihood, contributing one-fourth of gross domestic product and employing nearly 60% of the workforce [2]. This sector generates a large portion of export revenue and provides raw and intermediate inputs to various industries. Recently, Indian agriculture has experienced severe challenges from climate fluctuations, through a lack of adaptive capacity. Eckstein et al [3] announced India as the seventh most vulnerable nation to climate change on account of its diverse climatic regions. According to Ranuzzi and Srinivasan [4], future climate scenarios for the country include: 1) 2-4°C increment in mean surface temperature; 2) 1-4mm per day upsurge in the intensity of precipitation; 3) Higher variation in recurrence and distribution of seasonal rainfall; 4) a decrease in the number of rainy days lasting more than fifteen days; 5) more frequent and intense cyclones. Because of the changing climate, the total agricultural production and the national domestic product of the country are anticipated to reduce by 24 and 6.2%, respectively, towards 2080 [5]. Masters et al [6] also predicted that national agricultural revenue is estimated to decrease by 9-25% as temperature climbs by 2-3.5%. Apparently, the influence of meteorological factors on declining agricultural productivity differs by region [7]. Hence, agricultural productivity analysis is crucial from the perspective of climate effects, and it needs to be one of the policymakers' primary concerns. In addition to climate, socio-economic factors[1] and factors affecting technical change[2] also influence agricultural productivity.

A number of policies proved useful following the introduction of five-year plans to improve the agricultural growth rate in India, which was as low as 0.5% per year before 1950 [8]. The green revolution altered agricultural production patterns by introducing high yield variety (HYV) seeds, greater irrigation infrastructure investment, and modern fertilizers. With increased crop diversification and the introduction of new machineries (such as pump sets, tractors and tillers), agricultural productivity expanded. Productivity growth is both a necessary and sufficient condition for economic growth[3] [9]. However, given the recognized regional differences[4] in Indian agriculture, policies do not appear to be tailored based on the needs of the specific regions, thus requiring an

[1] Socioeconomic factors affecting agricultural productivity include urbanization, market accessibility, credit facilities, capital assets, mechanization, agricultural labourer education, fertilizer application, and government policies.

[2] Implementation of new technologies in agriculture, scientific innovation, government spending on R&D, the primary sector, and rural development are examples of factors affecting technological change.

[3] As a necessary condition, it prevents agriculture from succumbing to Ricardo's law of decreasing returns that is common in this industry. And, as a sufficient condition, it boosts output while cutting real-term unit costs.

[4] India is a vast country with a diverse range of agro-climatic zones and resource endowments. Because of varied levels of infrastructure and technological advancement, regional variations tend to become even more pronounced. Given regional disparities, with varying levels of productivity and technical advancement, homogeneous policies are found to be inappropriate.

evaluation of such productivity differences, and thus perhaps providing additional information for the formulation of relevant policies.

The conventional production function approach was initially used to analyze farm productivity. However, the approach was criticized because perfect efficiency was assumed in the modeling of the production process. The stochastic frontier approach, as an alternative, relaxes the assumption of perfect efficiency and provides more realistic results. Productivity can be divided into two categories: partial productivity and total factor productivity (TFP). The former assesses a single input's contribution to total output growth[5]; nevertheless, it does not accurately reflect whether the growth is caused by increased input use, increased input efficiency, or improved technology. Thus, the focus shifts to TFP, which measures total output growth per unit of the total input, with an increase in output that cannot be accounted for as being an indicator of input growth attributed to technical progress.

Using the production function method, Solow [10] initially calculated TFP as a residual after subtracting input growth from output growth, widely referred to as the Growth Accounting approach. However, the method fails to identify the drivers of TFP growth because it does not show whether increasing TFP is caused by technical efficiency or progress. Later, Ray and Desli [11] calculated the Malmquist productivity index[6] and deconstructed productivity growth into its constituent parts. But the non-parametric approach was unwarranted as it did not identify random shocks affecting output growth. In contrast, the stochastic frontier approach is parametric and takes random shocks into account, but it requires the specification of the error distributions. Furthermore, random shocks are handled better with panel data than with cross-sectional frontier models because the estimator takes into account additional data from multiple time periods [13].

The stochastic frontier production function method is used in this paper to measure productivity growth and technical efficiency for eighteen major crops in India, with four climate parameters serving as exogenous determinants, using an extensive district-level panel dataset from 1990 to 2015. Several studies [14–18] have estimated production frontiers to calculate productivity growth and identify its constituent parts; nevertheless, studies estimating TFP growth for manufacturing sectors cannot be extrapolated to primary sectors. Limited research has addressed larger questions about TFP growth, such as the role of technical change in determining output growth, and have outlined the development in conventional derivation and decomposition practice. Even less research has focused on the agricultural productivity of developing countries, incorporating the environmental shocks. This research has addressed the research gap, thus contributing to existing empirical research, and has analyzed TFP growth at the spatially disaggregated district level, spanning the entire country of India in terms of geographical coverage[7]. Further, to provide a larger sample, a longer time is being considered, which reduces the effect of random shocks on results. Besides the input-output relationship, estimation of a production frontier highlights the efficiency aspect of Indian agriculture and aids the analysis of those factors that might be directly affecting the

[5] Output growth corresponds to a rise in aggregate production, while productivity growth is used to model a firm's productive potential and evaluate capacity usage rates.
[6] Malmquist [12] developed a productivity index to determine changes in productivity.
[7] For broad geographies, analysis employing state-level panel data necessitates encoding climate variables with a single number. Furthermore, state-specific studies cover only a few districts and are hard to generalize.

production process. On the other hand, these factors can have the effect of lowering inefficiency in the production process.

The paper is structured as follows: Section 2 reviews the background literature, Section 3 presents the theoretical framework, Section 4 describes the data and methodology, Section 5 presents the results, and Section 6 concludes with suitable policy suggestions.

## 2 Brief literature

Abramovitz [19] reports that there are factors affecting output growth other than input growth; but Kendrick [20] claims that productivity growth is largely responsible for an apparent increase in production, which cannot be described by a rise in capital input. TFP growth, according to Solow [10], is a transition in the production function, which is typically considered to be a function of the rate of technical progress [21]. The idea gained traction after it was realized that long-term input increase had diminishing returns and would be unable to support large output growth [22]. Aigner et al [23] constructed a frontier model that shows that the TFP growth is driven by two factors: technical progress and changes in technical efficiency, with the benefit of easing the strict assumptions about firms functioning at optimal efficiency. By focusing on TFP decompositions, several studies [24–26] have identified the source of TFP growth. Kumbhakar and Lovell [27] divided TFP into four components: technical progress, allocative efficiency change, change in technical efficiency, and scale effect, using a flexible translog production function.

Recent studies [28–30] explored the correlation between climate change and TFP growth. These studies, which employed econometric methods, imply that climate change might be harmful to agricultural TFP growth, particularly in developing countries. These findings, nevertheless, suggest that the influence of changing climate on TFP growth is likely to differ by region and over time. Serval studies [31–34] focus on agricultural TFP growth of developing regions of China and sub-Saharan Africa. Though comparatively less research that focuses on south Asian countries is available, Southeast Asian agriculture is reported to have experienced a higher agricultural growth rate compared to south Asian countries [35]. Anik et al [36] estimated the agricultural TFP growth in India, Pakistan, Bangladesh, and Nepal, deconstructed the components of TFP growth, and reported that these Southeast Asian countries experienced sustainable growth in agriculture production for the period 1980-2013.

Either parametric or non-parametric methods have been used to evaluate and deconstruct the productivity growth of Indian agriculture since the early 1970s. Kalirajan [37] adopts a parametric approach and identifies agricultural productivity differences across farms of Coimbatore, a progressive district in Tamil Nadu. Sidhu and Byerlee [38] estimated annual TFP growth of 1.7% in Punjab (an agricultural-intensive northern state of India) over the period 1972-1984. Datta and Joshi [39] report that production efficiency in Aligarh (a district in Uttar Pradesh) for wheat and rice is 84% and 66%, respectively. Rosegrant and Evenson [40] studied the growth of agricultural TFP in India and Pakistan from 1956 to 1985, as well as the components of production growth. TFP growth was estimated to be 1.01% for India, explaining one-third of the net output growth in the agricultural sector. Expansion of irrigation, modern cultivation strategies, improved human capital, public and private research were stated as determinants of output growth. The authors indicate significant spillover benefit from private research.

Battese and Coelli [41] used ten years of panel data to undertake a frontier analysis and discovered that education boosts production efficiency in India, whereas aging diminishes it. Evenson et al [42] indicate that 30% of net TFP growth is explained by public agricultural research. Modern farm inputs, investment to expand irrigation and better rural markets were also considered as determinants of output growth. Using production frontier, Shanmugam [43] estimates the production efficiency of rice farming in Bihar lies between 36.7-98.1% and indicates high elasticity of farm inputs, such as fertilizer and land. Murgai [44] identifies the fundamental problems associated with traditional productivity measures, corrects the associated bias in technical change estimation, and indicates that TFP growth lies between 4-5%. Kumar et al [45] evaluate the agriculture sector's TFP growth on a regional basis and show the components of the TFP growth. According to the report, TFP growth declines at the Indo-Gangetic Plain, displaying strong indicators of unsustainable growth across several districts.

Coelli et al [46] studied the TFP growth of 93 countries, and, in the case of India, the annual TFP growth was recorded as 1.4%. According to Tripathi [47], agricultural growth between 1969 and 2005 was nearly entirely dependent on increases in traditional inputs, whereas productivity growth was negative. Only during the initial phases of agricultural reform was TFP growth beneficial. In the late 1990s, agricultural productivity in India appeared to have waned after two decades of rapid increase. India is not able to return to a path of sustained productivity growth unless major public and private investments are made in agriculture. Emerick [48] demonstrates exogenous gains in agricultural production due to higher than normal rainfall, using data from rural India. Furthermore, the study supports the theory that increased agricultural output leads to increased demand for locally produced non-tradeables, hence increasing the non-agricultural labour share.

Existing research on agricultural production and the components that affect it has produced useful theoretical foundations and empirical discoveries. Few studies have been conducted to investigate the trend in agricultural productivity growth in South Asia while taking environmental factors into account. Given the severity of climate change and southeast Asia's importance in the global economy and agriculture, there has been limited research on Indian agricultural productivity. Given that most earlier studies focused on single crops and that the models were region-specific, the present study fills the gap in the literature on Indian agricultural productivity at a spatially disaggregated level. A stochastic frontier model is adopted using panel data of 571 districts over a 26-year period to estimate agricultural productivity. This isolates statistical noise from anticipated productivity scores and thus provides supporting evidence to related literature in a parametric analytical framework.

# 3 Theoretical background

TFP is a productivity metric[8] that considers all production components. When partial (conventional) metrics of productivity, such as land productivity, are evaluated independently, they might lead to an inaccurate picture of overall production. TFP, also known as the Solow residual, is what remains after output growth less the weighted growth rate of inputs, presuming constant returns to scale. In

[8] Productivity is an essential aspect in analyzing a firm's performance. The ratio of output to input represents productivity, with higher ratio values indicating higher performance. When there are several inputs and outputs, productivity is calculated using aggregate measurements.

a competitive input market, if a technology has a rising or decreasing return to scale, the variation in TFP is decomposed into technical change, change in technical efficiency, and scale effect[9]. Efficiency change includes variation in both technical and allocative efficiency[10] [27]. The firm-specific variation in TFP can be estimated from the empirical production function. But, before that, TFP growth is deconstructed[11] to identify and address its components.

The stochastic production frontier, referring to Aigner et al [23] can be stated as:

$$q_{it} = f(x_{it}, \beta, t)e^{\varepsilon_{it}} \dots (1)$$

Where, $q_{it}$ indicates the total output in firm *i* at time *t*; $f(\cdot)$ indicates the frontier technology; $x_{it}$ indicates the vector of *k* inputs in firm *i* at time *t*; and $\beta$ indicates the vector of unknown parameters. If composite error term, $\varepsilon_{it} = v_{it} - u_{it}$ then Equation 1 is written as:

$$q_{it} = f(x_{it}, \beta, t)e^{v_{it}}e^{-u_{it}} \dots (2)$$

Where error components $v_{it}$ and $u_{it}$, respectively, capture shocks[12] that are beyond and under the control of the producer. Further, $z_{it}$ is a vector of *m* exogenous variables in district *i* at time *t* that influences $u_{it}$, and $\gamma$ is a vector of unknown coefficients. We can express $u_{it}$ as a function of those variables as:

$$u_{it} = f(z_{it}) + w_{it} \dots (3)$$

Where, $w_{it}$ is an error term determined by truncation[13] of $N\ (0, \sigma_u^2\ )$ distribution. In Equation 2, TIE varies over time. Given time as an independent variable, it captures the trend of variation in productivity. When $\sigma_v^2 = 0$, a deterministic production frontier can be obtained as:

$$q_{it} = f(x_{it}, \beta, t)e^{-u_{it}}$$

or:

$$\ln q_{it} = \ln f(x_{it}, \beta, t) - u_{it} \dots (4)$$

Totally differentiating with respect to time[14],

[9] Scale effect implies change in input use leading to output growth.
[10] Allocative efficiency is the process of integrating different inputs to form a range of outputs, while technical efficiency is simply focused on producing maximum output at the lowest possible cost.
[11] TFP decomposition determines whether more inputs, improved input use efficiency, or technical advancement contributed more to output growth. It is critical to distinguish between enhanced TFP in connection to technical progress and enhanced technical efficiency in the deployment of existing technologies from a policy standpoint.
[12] Both error components are independent of one another. Two-sided error component $v_{it}$, also known as statistical noise, is independent and identically distributed as $N\ (0, \sigma_v^2\ )$. One-sided error component $u_{it}$, representing technical inefficiency[12] (TIE), is an independent and identically distributed non-negative disturbance obtained from $N\ (z_{it}\gamma, \sigma_u^2\ )$ distribution truncated at zero [41].
[13] Truncation happens at $-\gamma z_{it}$, causing $u_{it}$ to be non-negative.
[14] Notational cluster is avoided by excluding *i* and *t* subscripts.

$$\frac{\partial}{\partial t}\ln\ q\ = \frac{\partial}{\partial t}\ \ln\ \ f(x\ ,\beta ,t) + \sum \frac{\partial}{\partial x_k}\ \ln\ \ f(x\ ,\beta ,t)\frac{\partial x_k}{\partial t} - \frac{\partial u}{\partial t}$$

Or,

$$\dot{q}\ = TC + \sum \epsilon_k \dot{x}_k + \dot{TE}\ \dots (5)$$

Where, $\epsilon_k = \frac{\partial}{\partial x_k}\ \ln f(\cdot)$ is the output elasticity of input *k*. Technical progress, also termed as technical change ($TC = \frac{\partial}{\partial t}\ \ln f(\cdot)$), variation in input use (scale efficiency), and variation in technical efficiency[15] ($\dot{TE} = -\frac{\partial u}{\partial t}$), determines Output growth ($\dot{q}$ ). Variation in scale effect (SE) is alternatively estimated as the difference between $\dot{q}$ and $T\dot{F}P$, referring Kalirajan and Shand [49], where $T\dot{F}P$ is measured by the sum of $TC$ and $\dot{TE}$.

In Figure 1, *F1* and *F2* are production frontiers of a firm in time periods 1 and 2, respectively. If TE exhibits, the outputs for time periods, 1 and 2 would be *q1* and *q2*, respectively. If the firm does not operate in frontier, then the actual output is *q3* and *q4* in time periods 1 and 2. TIE, which is *q1-q3* in period 1 and *q2-q4* in period 2, could be the cause. If TC exhibits in period 1, then more output is produced with the same input that shifts firm frontier to *F2*. For *x1* inputs, the firm output would be *q5,* and TC is *q5-q1*. By identifying the contribution of input growth to output growth as *q2-q5*, total output growth is deconstructed as:

$$\begin{aligned}\dot{q}\ = (q4 - q3) &= (q1 - q3) +\ (q5 - q1) +\ (q4 - q5)\\ &= (q1 - q3) +\ (q5 - q1) +\ (q4 - q5 + q2 - q2)\\ &= (q1 - q3) +\ (q5 - q1) +\ (q2 - q5) -\ (q2 - q4)\\ &= [(q1 - q3) -\ (q2 - q4)] +\ (q5 - q1) +\ (q2 - q5) = \dot{TE} + TC + SE \dots (6)\end{aligned}$$

Again, $T\dot{F}P$ as a difference between the change in observed output and an aggregate measure of observed input usage can be written as:

$$T\dot{F}P = \dot{q}\ - \sum \frac{p_k x_k}{c} \dot{x}_k \dots (7)$$

Where, $p_k$ is the input price of $x_k$ while *c* is the actual cost. By substituting $\dot{q}$ from Equation 5 in Equation 7:

$$T\dot{F}P = TC + \sum \epsilon_k \dot{x}_k + \dot{TE} - \sum s_k\, \dot{x}_k$$

$$= TC + \dot{TE} + (\epsilon\ - 1) \sum \tau_k \dot{x}_k + \sum (\tau_k - s_k)\, \dot{x}_k \dots (8)$$

[15] Technical efficiency (TE) is a crucial facet of evaluating firm performance. A technically efficient firm operates on the frontier to maximize output, given specified quantity of inputs. A firm is said to be 100% efficient if its actual output meets its potential frontier output. A firm that is technically inefficient operates below the frontier. Because no firm operates above the frontier level, TE and TIE range from 0 to 1, and $TE + TIE = 1$.

Where, $\epsilon = \sum \epsilon_k$ indicates a measurement of returns to scale, $s_k = \frac{p_k x_k}{c}$ is the share of input *k* in production cost, and $\tau_k = \epsilon_k/\epsilon$. If a constant return to scale is exhibited, then $\epsilon = 1$. The last term in Equation 8 denotes allocative efficiency, which is incalculable because cost information is unavailable. In that case, referring to Kumbhakar et al [27] and assuming $\tau_k = s_k$, Equation 8 is rewritten as:

$$T\dot{F}P = TC + T\dot{E} + (\epsilon - 1)\sum \frac{\epsilon_k}{\epsilon}\dot{x}_k \ldots (9)$$

# 4 Material and method

## 4.1 Agricultural data

In this work, a comprehensive spatially disaggregated district-level dataset has been employed for the period spanning from 1990-91 to 2015-16; districts being the lower administrative divisions with access to reliable agricultural data. For the present analysis, annual agricultural input and output data from the International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) database is used. The data was primarily obtained from the Indian government's Directorate of Economics and Statistics and the State Directorate of Agriculture. The dataset covers district boundaries of 20 Indian states (Andhra Pradesh, Gujarat, Bihar, Haryana, Madhya Pradesh, Karnataka, Maharashtra, Punjab, Odisha, Rajasthan, Uttar Pradesh, Tamil Nadu, West Bengal, Jharkhand, Chhattisgarh, Uttarakhand, Himachal Pradesh, Assam, Kerala and Telangana) in 2015, and consists of 571 districts in total. Eighteen categories of crops are considered: rice, sorghum, wheat, maize, pearl millet, finger millet, chickpea, barley, pigeon pea, sesamum, groundnut, rapeseed and mustard, linseed, castor, sunflower, sugarcane, soybean and cotton. Each crop contributes significantly to India's total agricultural output. The total agricultural production (in thousand tons) is approached through aggregating the net production of each crop under study. Gross cropped area (in thousand hectares), Total agricultural labour (in thousand numbers), number of tractors used (in thousand numbers), and total fertilizer consumption (in tons), are the independent variables of interest that is classified as land, labour, capital and fertilizer, respectively. Fertilizer data is obtained from India's Fertilizer Association, which includes a total of nitrogen, phosphate, and potash fertilizer consumption. Labour data is obtained from the census dataset from the Registrar General of India. Because labour data was only available for 1991, 2001, and 2011, the sample data was interpolated for other years by fitting a linear trend onto a population growth.

## 4.2 Weather data

Extensive district-level annual meteorological data for this study was also sourced from the ICRISAT database, which was essentially derived from the Terra climate data archive. The latter contains monthly temporal and high-spatial (1/24 degree, nearly 4 kilometers) resolution weather data for global terrestrial surfaces from 1958 to 2019. Initial NetCDF (Network Common Data Form) data is converted to GeoTIFF (Geographic Tagged Image File Format) format using ArcGIS software. These layers are aggregated using Zonal Statistics as a table. Mean statistics are used to aggregate the pixels to the district-level. The data from 1958-2019 is processed in batch mode to obtain yearly tables for each weather variable at the country-level. Finally, yearly files are integrated into a single Excel sheet using an R-script. The independent weather variables generated from the database are monthly rainfall (in millimeters), windspeed (in meters per second), evapotranspiration (in millimeters), and average temperature (in degrees Celsius). Average monthly temperature is the mean of the monthly minimum and maximum temperature obtained from the database. To study the influence of weather shocks, annual weather variables are computed and defined climate parameters as exogenous determinates of technical inefficiency term.

## 4.3 Methodology

The translog functional form[16] is a widely-used specification that approximates any arbitrary functional form with a local second-order approximation. With reference to Equation 1, the time-varying production frontier in translog form can be written as follows:

$$\ln q_{it} = \alpha_0 + \sum \alpha_k \ln x_{kit} + \alpha_t t + \tfrac{1}{2}\sum\sum \beta_{kl} \ln x_{jit} \ln x_{kit} + \tfrac{1}{2}\beta_{tt} t^2 + \sum t\beta_{tk} \ln x_{kit} + v_{it} - u_{it} \dots (10)$$

Where, $q_{it}$ indicates the value of actual output in district *i* at time *t*; *x* indicates input variables; *t* indicates the time trend; differences in productivity across *i* and *t* are assumed to be captured in $\alpha_k$ and $\beta_{tk}$; structure of input substitution possibilities is characterized by $\beta_{kl}$; and $v_{it}$ and $u_{it}$ represents error components. The observation-specific one-sided error $u_{it}$ is under the domination of the production unit and influences TE, while the statistical noise $v_{it}$ is not under the domination of the production unit. Referring to Battese & Coelli [52], an exponential function of time is used to model the observation-specific error:

$$u_{it} = \lambda_t u_i = u_i e^{-\lambda(t-T)} \dots (11)$$

Where, $t = 1,2,\dots,T$; $i = 1,2,\dots,N$; $\lambda$ represents an unknown parameter that indicates the variation in $u_i$ of a firm *i* in the final year of the time series, which accounts all technical inefficacies of the firm before T. If $\lambda$ is positive, then that implies improvement in the efficiency level; alternatively, if it is negative, it indicates deterioration in the efficiency level. No time-varying TIE is exhibited when $\lambda$ is zero.

For the present study, the following functional specification is adopted for analysis:

$$\begin{aligned}\ln q_{it} = {} & \alpha_0 + \alpha_a \ln A_{it} + \alpha_l \ln L_{it} + \alpha_k \ln K_{it} + \alpha_W \ln W_{it} + \frac{1}{2}\beta_{aa}(\ln A_{it})^2 + \frac{1}{2}\beta_{ll}(\ln L_{it})^2 \\ & + \frac{1}{2}\beta_{kk}(\ln K_{it})^2 + \frac{1}{2}\beta_{WW}(\ln W_{it})^2 + \beta_{al}\, lnA_{it} \ln L_{it} + \beta_{ak}\, lnA_{it} \ln K_{it} \\ & + \beta_{aw}\, lnA_{it} \ln W_{it} + \beta_{lk}\, lnL_{it} \ln K_{it} + \beta_{lw}\, lnL_{it} \ln W_{it} + \beta_{kw}\, lnK_{it} \ln W_{it} \\ & + \beta_{ta}(\ln A_{it})t + \beta_{tl}(\ln L_{it})t + \beta_{tk}(\ln K_{it})t + \beta_{tW}(\ln W_{it})t + \alpha_t t + \frac{1}{2}\beta_{tt} t^2 + v_{it} \\ & - u_{it} \dots (12)\end{aligned}$$

where, $q_{it}$ is the observed total agricultural output level of district *i* in time *t*; *A*, *L*, *K* and *W* represent land, labour, capital and fertilizer, respectively. The TE is calculated as the ratio of observed output

[16] Initially developed and extensively used by Christensen et al [50], trans-log specification is commonly used by researchers, such as Mari and Lohano [51], as it allows technical changes to be factor-augmenting.

to potential frontier output. As a result, the technical efficiency of district *i* in period *t* can be evaluated as follows:

$$TE_{it} = e^{-u_{it}} \dots (13)$$

Technical efficiency change (TEC) is nothing but the change in TE, i.e., $\dot{TE}$ . Referring to Equation 3, functional form of exogenous determinates of $u_{it}$ is expressed as:

$$u_{it} = \gamma_0 + \gamma_1 Z_{it} + w_{it} \dots (14)$$

Where, *Z* indicates the vector of climate parameters under the study and $w_{it}$ is the measurement error. Climate variables, despite being exogenous, have an effect on agricultural productivity and are thus included in the production function.

Referring to the theoretical framework, TC and SE for district *i* in time *t* are estimated as:

$$TC_{it} = \frac{\partial}{\partial t} \ln q_{it} = \beta_{ta}(\ln A_{it}) + \beta_{tl}(\ln L_{it}) + \beta_{tk}(\ln K_{it}) + \beta_{tW}(\ln W_{it}) + \alpha_t + \beta_{tt} t \ \dots (15)$$

$$SE = \dot{q} - (\dot{TE} + TP) \dots (16)$$

Initially, Jondrow et al [53] suggested estimating the mode or mean of the conditional distribution of $u_i$ given , $\varepsilon_i$ as a point estimate of $u_i$. Further, Battese & Coelli [41] improved the approach in frontier analysis[17] to accommodate panel data and recommended a single-stage simultaneous estimating method in which independent variables are directly incorporated into the inefficiency error term. A two-stage approach[18] was adopted in preliminary studies [37,54]. However, the approach is criticized as second-stage regression is likely to be downward-biased [55].

This study adopted the True Fixed Effect (TFE) method proposed by Greene [56] due to its relative advantages over other available models. The earlier models [41,52] were unable to separate the time-invariant and unit-specific unobserved heterogeneity from time-varying inefficiency resulting in a biased estimate of inefficiency. The inefficiency effect and the time-invariant firm-specific effect should be assessed separately while estimating the models. If firm-specific heterogeneity is not properly segregated, the estimated inefficiency might include both inefficiency and firm-specific heterogeneity. Therefore, it is difficult to conduct empirical research when models are incapable of estimating individual effects on top of the inefficiency effect.

To deal with these issues, this study has adopted the TFE model, which has the advantage of estimating technical efficiency by separating the inefficiency term (which varies over time) from the unit-specific heterogeneity. The TFE model is a conventional fixed effect panel model with a one-

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[17] Apart from frontier analysis, data envelopment analysis (a non-parametric deterministic approach) such as corrected mean absolute deviation (CMAD) and corrected ordinary linear system (COLS), can be used to evaluate TE. This approach presumes that all deviations from the frontier are due to TIE, and thus fails to acknowledge other random shocks (statistical noise). Stochastic frontier analysis, on the other hand, is a parametric approach that accounts for both statistical noise (two-sided error) and TIE (one-sided error) effects.
[18] Efficiency scores are generated in the first stage by estimating a stochastic frontier function. In the subsequent stage, computed efficiencies are regressed against a vector of independent factors using conventional least square regression.

sided error term[19]. As a result, though, Battese and Coelli's [52] model is estimated, which was unable to incorporate the exogenous determinants, and Battese and Coelli's [41] model with capabilities to include exogenous determinants, current analysis restricts to the TFE model for the above-mentioned reasons. Moreover, the maximum likelihood estimation procedure is adopted considering a flexible translog production function following a truncated normal distribution[20] for $u_{it}$. Dummy variables are used to illustrate heterogeneity in the model, and the problem of statistical noise is confronted, leading to inconsistent variance estimates[21]. However, the frontier coefficients are not affected by the problem.

# 5 Results

All estimates in the present analysis are performed using the statistical software STATA 17. Agricultural productivity growth for India has been estimated across states and over time, assuming a translog production function. Table 1 provides the estimated results of the panel frontier model. Coefficients of district dummies are repressed to conserve space. The TFE model[22] is chosen to account for climate variability, as it has the advantage of accounting for z-variables related to exogenous weather shocks. Aside from being climate-sensitive, agriculture is a highly regulated sector in the country, where both central and state governments[23] implement policy controls to ensure adequate food supply, maintain the economic viability of the rural business, expand agricultural export, protect marginal farmers and respond to the farmer and food problems. Hence, the period considered in the present study gives proof of several reforms that could have potentially affected the productivity growth of Indian agriculture.

Productivity growth has been decomposed into technical progress, technical efficiency changes, and scale efficiency change. The evaluated TFP growth between 1990 and 2015 is found to be averaged at 0.688%, consisting of 0.004% of technical progress, 0.384% of the change in technical efficiency and 0.293% of scale operation (Table 2). Table 3 represents the year-wise and state-wise mean technical efficiency scores. The estimated mean technical efficiency is found to be 0.930%, representing production units operating at nearly 93% of their potential output. The mean technical efficiency score exhibits significant volatility over the period, with states like Punjab, Kerala, Himachal Pradesh, and Assam having efficiency scores of more than 96%[24] (Figure 2.1 and 2.2). In 2002, technical efficiency was at its lowest, given slow productivity growth. The latter could be attributed to existing technology becoming obsolete given weather shocks.

[19] Mean of the error term is a function of $u_{it}$.

[20] Other than half-normal distribution, in empirical research, exponential and truncated normal distributions are also assumed for $u_{it}$. The assumption about distribution serves in determining TIE of the production function. Greene [57] recommends truncated normal distribution (with heterogeneity in the mean) that makes modelling tools more flexible.

[21] In frontier analysis, error variances influence the derivation of inefficiency scores [53]

[22] The parameters such as $\lambda$ and $\gamma$ play key roles in model selection in frontier model estimation. The original parameters ${\sigma_u}^2$ and ${\sigma_v}^2$ estimated from the estimates of variance parameters $\sigma_u$ and $\sigma_v$, respectively. The transformation from $\sigma_u$ and $\sigma_v$ to ${\sigma_u}^2$ and ${\sigma_v}^2$ can only be done if they are constant. In the present analysis, $\sigma_u$ is a function of a set of weather variables. As a result, measurement of ${\sigma_u}^2$ is practically difficult and due to which $\lambda$ and $\gamma$ are not presented.

[23] State government retains the constitutional authority over the sector.

[24] Uttarakhand is excluded from the present analysis since corresponding estimates were deemed outliers.

The contribution of TFP growth to output growth over the year is shown in Table 4.1, along with the determinants of productivity growth. In 1991, the TFP growth rate is 1.192%, consisting of 0.004% technical progress, 0.378% technical efficiency change and 0.810% scale effect. Productivity growth initially drops, falling from 1.192% in 1991 to 0.809% in 1993 and then exhibits a sharp increase of 7.317% between 1993 and 1995. Between 1995 and 2000, productivity growth again declines, falling from 0.476% in 1995 to 0.250% in 2000. Moreover, TFP growth shows a downward trend between 1990 and 2000, except for a dramatic spike in productivity growth between 1993 and 1995 (Figure 3.4). Though technical progress increases over the period, the decline in output growth is primarily due to the deterioration in scale efficiency, which drops from 0.810% in 1991 to -0.156 in 2000. After many decades of consistent output growth[25], the focus of the policies shifted to enhancing the function of the market, lowering superfluous legislation, and liberalizing agricultural trade. Unlike agricultural reform in other developing counties, a series of agricultural reforms implemented in the 1990s left the rural and agricultural sectors relatively untouched [58,59]. Kalirajan et al [60] further indicate two potential reasons for the decline in output growth: the lack of major innovation in developing HYV seeds and the degradation in the environmental quality of land, which lowered the marginal productivity of the inputs engaged in production. Given a lack of input delivery method, infrastructure facilities, and technical slack, changing cropping patterns and area expansion were the only bounded contributors to output growth during the 1990s [61]. Nevertheless, between 1993 and 1995, a sharp increase in TFP growth is marked. Even though technical efficiency changes decline, this increase in productivity growth mainly consists of an appreciation in scale component, which is about 94% of total TFP growth in 1994. After the Small Farmers Agribusiness Consortium was formed in 1994, fiscal actions such as increased input subsidies and trade protection, increased crop diversification, and the contribution of output prices could have attributed to a brief surge in TFP growth [58]. However, the downward trend recovered as the legislative focus changed and also because the constant increase in the output price is never a long-term driver of productivity growth [62].

TFP growth exhibits an ascending trend between 2000 and 2006, which rises from 0.250% in 2000 to 1.793% in 2006. In 2000, the government of India published the National Agricultural Policy. This aimed to increase annual crop productivity of over 4% through resource efficiency in order that it would meet the rising domestic demand for agricultural products and also maximize agricultural export benefits. This would overcome challenges that had emerged from liberalization [63,64]. The reform further included initiatives such as efficient use of natural resources, water and soil conservation, demand-driven growth catering to the domestic market, sustainable technological advancement, and economic growth with equality [58]. Given that the overall agricultural investment remains low, the above reform in domestic regulation promotes the incentive for rising private investment in the agricultural sector, hence increasing output growth [65]. However, a steep drop in productivity growth is marked between 2004 and 2006. In 2005, the output growth measure was -1.839%, consisting of 0.004% technical progress, 0.357% technical efficiency change and -2.185% scale effect. This major drop in output growth was caused by a deterioration in technical

[25] Initially formulated policies, after independence, focused on community development, land reforms, cultivated area expansion and community development. Substantial agricultural policy measures (such as of trade protection measures, minimum support price, input subsidy and food grain distribution and procurement) adopted in mid-1960s, significantly increased agricultural production in India for several decades.

efficiency as well as in the scale of operation in the relevant years. States that initially benefited from the post-green revolution showed a decline in productivity growth in 2005 due to scale inefficiency. There was a decreasing share of conventional inputs use caused by an increasing value of modern inputs. The cost of inputs limits farmers who want to integrate new inventions into their input combination. Because of the increasing use of machinery, higher technical efficiency[26], widespread employment opportunities in the service sector, and the implementation of the Mahatma Gandhi National Rural Employment Guarantee Act, the share of agricultural labour inputs declined in 2005, reducing output growth [66,67]. Also, productivity was reported to abate because of a severe drought in 2003 followed by a recession till 2005, and a falling share of fertilizer, seed and pesticides, caused by a rising value of other inputs such as machinery costs and imported diesel in the year being considered [66].

Productivity growth is estimated to be 1.793% in 2006, followed by a descending trend from 2007 to 2015, with limited fluctuations. Output growth fell from 0.588% in 2007 to 0.348% in 2015, attributable to a decline in scale operation. In 2015, the productivity growth measure was 0.348%, with 0.004% of technical progress, 0.389% of technical efficiency change, and -0.034% of scale component. Indian agricultural TFP growth is primarily caused by public investment in infrastructures such as roads, electricity and irrigation, as well as government expenditure in education, human capital development and advancement in agricultural research and extension. The measured drop in TFP growth was caused by a significant reduction in investments in India's agriculture, particularly public-sector investments [68]. Other than that, rising population creating greater pressure on land, uneconomic holdings with one-fourth of rural farmers owning less than 0.4 hectares each, climate hazard, an uncertain monsoon coupled with insufficient irrigation facilities, diminishing return to input use, stagnation in the gross cropped area, traditional methods of farming, degradation of soil quality and lack of effective institutional support services (such as credit facilities and marketing), and faulty trade policies were all potential reasons behind the decline in productivity growth [58,64,68]. In addition to determinants of TFP growth, weather characteristics also affected the TFP growth of climate-vulnerable regions. Agricultural TFP growth reduces or grows slowly in dryer years, increases in cooler years, and grows to some extent in wetter years [69].

Table 4.2 depicts the TFP growth across states from 1990 to 2015, along with its determinants. Tamil Nadu has the highest rate of output growth, followed by Himachal Pradesh, Andhra Pradesh, Rajasthan, Telangana, and Gujarat (Figure 4.4). TFP growth rate in Tamil Nadu is 2.174%, which consists of 0.004% technical progress, 0.825% technical efficiency change, and 1.341% scale effect. Tamil Nadu, which benefits from two monsoons, has excellent harvests of rice, oilseeds, and sugarcane [70]. The main driver of this large output growth in Tamil Nadu and Himachal Pradesh is due to an advancement in scale efficiency during the relevant period, compared to other states. Higher productivity scores in Rajasthan, Telangana, Gujarat and Andhra Pradesh are primarily due to progress in technical efficiency change. Northern states such as Himachal Pradesh and Rajasthan experienced outstanding growth in agricultural production due to efficient irrigation facilities and structured marketing facilities. Andhra Pradesh contributes to climate-resilient crop cultivation, with most of the workforce engaged in agriculture [71,72]. Assam, Punjab, and Jharkhand have low productivity scores, while Karnataka has the lowest productivity growth of -0.873% among all states,

[26] Globalization combined with increased technical efficiency leads to lower labour share in agriculture.

owing to a decline in scale efficiency over the period. Technical progress, rather than input growth, accounts for agricultural output in Karnataka, a state experiencing frequent droughts. Farmers are responsible for the inclusion and efficient use of agricultural inputs. The reason for observed output falling short of the frontier level is the inefficient resource utilization and frequent crop failure due to environmental degradation [73,74]. Also, in Karnataka, government-implemented measures failed to protect farmers, resulting in an upsurge in farmer suicide [75]. Primary problems impeding the development of the agricultural sector in Assam and Jharkhand include continued dependence on rain for irrigation, lack of modern equipment, and land fragmentation [76]. Jharkhand, however, has a positive TFP growth rate due to comparatively better resource use and higher technical progress. Similarly, the primary cause of the lower output growth in Punjab and Assam is deterioration in scale components. The negative scale effect also affects Gujarat, Andhra Pradesh, and Maharashtra, but significant improvements in technical efficiency have mitigated the adverse effects on output growth. Most output growth is due to changes in technological efficiency, while yearly and cross-state productivity growth inequalities are attributable to differences in scale components.

Turning now to the disintegrated determinants of TFP growth, overall technical progress does not show a significant difference over the year (Figure 3.1), whereas changes in technical efficiency show a high degree of volatility (Figure 3.2). Scale component shows a descending trend over time yet exhibits abrupt increase between 1993 and 1995 and decrease between 2004 and 2006 (Figure 3.3), and in fact, follows the trend of TFP growth. Moreover, scale operation is affected by agroclimatic conditions, weather, and the size of the farm. Relatively large farm sizes are advantageous because input combination and growth frequently vary with farm size [77]. Tamil Nadu ranks first with a scale effect of 1.341%, followed by Himachal Pradesh, whilst Karnataka stands last with a scale effect of -1.174% due to incompetent resource utilization (Figure 4.3). Negative scale effects can also be seen in Andhra Pradesh, Assam, Gujarat, Jharkhand, Maharashtra, Rajasthan and Punjab. Agricultural productivity growth in Punjab was widely acclaimed during the Green Revolution of the 1960s, but recent reports indicate a disturbing trend in Punjab agriculture due to environmental degradation-led water challenges [78]. The economic conditions of the farmers have deteriorated because present farming systems and technologies are highly exploited. Stagnating productivity, pest outbreaks, deficiency in soil micronutrients and a diminishing water table have been reported in Punjab [79]. On the contrary, Bihar, once labelled as a backward state, is now taking the limelight at the national level, leading the way with the highest technical progress with significant agricultural productivity and relatively high private investment in yield-augmenting inputs [80]. Bihar leads the way with technical progress of 0.005%, followed by Jharkhand, Andhra Pradesh, and Madhya Pradesh (Figure 4.1). Technical progress in states such as Uttar Pradesh, Telangana, Tamil Nadu, Rajasthan, Maharashtra, Karnataka, Gujarat, and Chhattisgarh exceeds 0.004%. Technical progress is often accompanied by increased government spending on R&D, which results in innovation [81]. Himachal Pradesh has the lowest score for technical progress and change in technical efficiency. Tamil Nadu leads the way with a technical efficiency change of 0.825%, followed by Andhra Pradesh, Gujarat, Rajasthan, and Telangana (Figure 4.2). Farmers in states with wider agricultural extension services are better equipped to manage and improve their technical efficiency by using existing technologies [77,81]. Heterogenous production performance across states is clearly due to disparities in physical endowments, environmental conditions, and institutional traits. As a result, broad economic reforms are less likely to succeed than state-specific policy initiatives that allow each state's agricultural production to attain its full potential.

## 6 Conclusion

Optimizing agricultural productivity, a key determinant of food security, is a primary concern for emerging nations seeking long-term economic growth. Agriculture plays a pivotal role in India, contributing a significant portion to the country's gross domestic product and employing nearly 60% of the total population. Using a stochastic production frontier model, this paper examined the growth of agricultural productivity in twenty major states of India from 1990 to 2015. The many causes of productivity growth, including technical progress, change in technical efficiency, and scale effects, have been discovered through the deconstruction of TFP growth.

India experienced a decline in agricultural productivity between 1991 and 2000. After the advent of the national agricultural policy, productivity improved between 2000 to 2006. However, due to a significant reduction in public investments in the primary sector, agricultural productivity declined between 2007 to 2015. Technical efficiency changes made a significant contribution to Indian agricultural TFP growth, followed by scale efficiency changes. Though certain states, such as Bihar, Tamil Nadu, and Uttar Pradesh, made notable changes in terms of technical progress, the overall picture of India's agricultural productivity is not very impressive. Growing environmental stress, fragmented land-use patterns and long supply chains, weak linkages to input markets and domestic downstream sectors, limited participation scope in regional and global value chains, rising population pressure and nutrition insecurity are the main reasons for India's agricultural productivity growth lagging behind that of other emerging countries [65].

States with low technical advancement need the adoption of cutting-edge technology with improved resource allocation. Considering that scale effects are a major contributor to the decline in output growth in certain states, strengthening management skills, promoting the efficient use of available inputs, and regulating structural constraints (such as farm size, age and weather elements) can help improve scale operation. Given marginal farmers are unable to afford the cost of modern inputs and often fail to switch to prevailing technologies [82], O'Donnell [81] suggests improvements in terms of trade that could increase technical efficiency and scale operation, and thus profitability. Investments that can bring newly developed technologies and improve the efficient use of existing technology should be encouraged by government policy. Given the importance of climate in crop productivity, environmentally friendly and climate-resilient farming such as crop diversification should be promoted to increase productivity and resilience in rural agriculture. Based on present findings, policymakers should strengthen the infrastructure base, particularly in the rural regions, which is critical for increasing the performance of Indian agriculture. This is conceivable since there is much potential for optimizing the available resource base. To improve India's agricultural position, it would be necessary to invest in technological advancements, research, and development. It is also recommended that policies should be differentiated, taking account of regional disparities. This would be helpful for each production unit in different regions to become more efficient and allow them to converge in terms of productivity.

## References


[1] R.K. Pachauri, M.R. Allen, V.R. Barros, J. Broome, W. Cramer, R. Christ, J.A. Church, L. Clarke, Q. Dahe, P. Dasgupta, N.K. Dubash, O. Edenhofer, I. Elgizouli, C.B. Field, P. Forster, P. Friedlingstein, J. Fuglestvedt, L. Gomez-Echeverri, S. Hallegatte, G. Hegerl, M. Howden, K. Jiang, B. Jimenez Cisneroz, V. Kattsov, H. Lee, K.J. Mach, J. Marotzke, M.D. Mastrandrea, L. Meyer, J. Minx, Y. Mulugetta, K. O'Brien, M. Oppenheimer, J.J. Pereira, R. Pichs-Madruga, G.-K. Plattner, H.-O. Pörtner, S.B. Power, B. Preston, N.H. Ravindranath, A. Reisinger, K. Riahi, M. Rusticucci, R. Scholes, K. Seyboth, Y. Sokona, R. Stavins, T.F. Stocker, P. Tschakert, D. van Vuuren, J.-P. van Ypserle, Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, IPCC, Geneva, Switzerland, 2014. https://epic.awi.de/id/eprint/37530/ (accessed July 16, 2021).

[2] S. Kadiyala, J. Harris, D. Headey, S. Yosef, S. Gillespie, Agriculture and nutrition in India: mapping evidence to pathways, Annals of the New York Academy of Sciences. 1331 (2014) 43–56. https://doi.org/10.1111/nyas.12477.

[3] D. Eckstein, V. Künzel, L. Schäfer, Global Climate Risk Index 2021, Germanwatch, Germany, 2021. https://germanwatch.org/en/19777 (accessed December 17, 2021).

[4] A. Ranuzzi, S. Srinivasan, Impact of climate change on agriculture and food security, ICRIER, New Delhi, 2012.

[5] F. Zhai, T. Lin, E. Byambadorj, A General Equilibrium Analysis of the Impact of Climate Change on Agriculture in the People's Republic of China, Asian Development Review. 26–1 (2009) 206–225. https://ideas.repec.org/a/ris/adbadr/2617.html (accessed December 19, 2021).

[6] G. Masters, P. Baker, J. Flood, Climate change and agricultural commodities, 2010.

[7] K.N. Ninan, S. Bedamatta, Climate change, agriculture, poverty and livelihoods: a status report, Institute for Social and Economic Change, Bangalore, 2012.

[8] G.S. Bhalla, G. Singh, Indian agriculture: four decades of development., Indian Agriculture: Four Decades of Development. (2001). https://www.cabdirect.org/cabdirect/abstract/20013086229 (accessed July 16, 2021).

[9] D. Saikia, Total Factor Productivity in Indian Agriculture: Some Conceptual and Methodological Issues, (2009). https://mpra.ub.uni-muenchen.de/28578/ (accessed July 16, 2021).

[10] R.M. Solow, Technical Change and the Aggregate Production Function, The Review of Economics and Statistics. 39 (1957) 312–320. https://doi.org/10.2307/1926047.

[11] S.C. Ray, E. Desli, Productivity growth, technical progress, and efficiency change in industrialized countries: comment, The American Economic Review. 87 (1997) 1033–1039. https://www.jstor.org/stable/2951340 (accessed July 17, 2021).

[12] S. Malmquist, Index numbers and indifference surfaces, Trabajos de Estadistica. 4 (1953) 209–242. https://doi.org/10.1007/BF03006863.

[13] J. Ruggiero, A comparison of DEA and the stochastic frontier model using panel data, International Transactions in Operational Research. 14 (2007) 259–266. https://doi.org/10.1111/j.1475-3995.2007.00585.x.

[14] S. Kim, G. Han, A Decomposition of Total Factor Productivity Growth in Korean Manufacturing Industries: A Stochastic Frontier Approach, Journal of Productivity Analysis. 16 (2001) 269–281.

[15] S.C. Kumbhakar, C.A.K. Lovell, Stochastic Frontier Analysis, Cambridge University Press, Cambridge, 2000. https://doi.org/10.1017/CBO9781139174411.

[16] P.K. Roy, P.S. Das, M.K. Pal, Decomposition of Total Factor Productivity Growth of the 2-Digit Manufacturing Industries in West Bengal: A Stochastic Frontier Approach, Arthaniti: Journal of Economic Theory and Practice. 16 (2017) 101–124. https://doi.org/10.1177/0976747920170104.
[17] A.K. Sahoo, N.C. Sahu, D. Sahoo, Impact of policy reforms on the productivity growth of Indian coal mining: A decomposition analysis, Resources Policy. 59 (2018) 460–467. https://doi.org/10.1016/j.resourpol.2018.08.019.
[18] S.C. Sharma, K. Sylwester, H. Margono, Decomposition of total factor productivity growth in U.S. states, The Quarterly Review of Economics and Finance. 47 (2007) 215–241. https://doi.org/10.1016/j.qref.2006.08.001.
[19] M. Abramovitz, Resource and output tends in the United States since 1870, National Bureau of Economic Research, Inc, 1956. https://econpapers.repec.org/bookchap/nbrnberch/5650.htm (accessed July 22, 2021).
[20] J.W. Kendrick, Productivity trends: capital and labor, The Review of Economics and Statistics. 38 (1956) 248–257. https://doi.org/10.2307/1925777.
[21] P. Krugman, The Age of Diminished Expectations, 3rd ed., MIT Press, Cambridge, MA, USA, 1997.
[22] R. Mahadevan, To Measure or Not To Measure Total Factor Productivity Growth?, Oxford Development Studies. 31 (2003) 365–378. https://doi.org/10.1080/1360081032000111742.
[23] D. Aigner, C. Lovell, P. Schmidt, Formulation and estimation of stochastic frontier production function models, Journal of Econometrics. 6 (1977) 21–37. https://econpapers.repec.org/article/eeeeconom/v_3a6_3ay_3a1977_3ai_3a1_3ap_3a21-37.htm (accessed September 2, 2021).
[24] B. Domazlicky, W. L., Determinants of Total Factor Productivity, Technological Change, and Efficiency Differentials Among States, 1977-86, The Review of Regional Studies. 28 (1998) 19–34.
[25] F. Fecher-Bourgeois, S. Perelman, Productivity growth and technical efficiency in OECD industrial activities, (1992). https://orbi.uliege.be/handle/2268/35656 (accessed July 22, 2021).
[26] S. Kumbhakar, Production frontiers, panel data, and time-varying technical inefficiency, Journal of Econometrics. 46 (1990) 201–211.
[27] S.C. Kumbhakar, M. Denny, M. Fuss, Estimation and decomposition of productivity change when production is not efficient: a paneldata approach, Econometric Reviews. 19 (2000) 312–320. https://doi.org/10.1080/07474930008800481.
[28] M. Henseler, I. Schumacher, The impact of weather on economic growth and its production factors, Climatic Change. 154 (2019) 417–433.
[29] S. Kumar, M. Khanna, Temperature and production efficiency growth: empirical evidence, Climatic Change. 156 (2019) 209–229.
[30] X.-Z. Liang, Y. Wu, R.G. Chambers, D.L. Schmoldt, W. Gao, C. Liu, Y.-A. Liu, C. Sun, J.A. Kennedy, Determining climate effects on US total agricultural productivity, PNAS. 114 (2017) E2285–E2292. https://doi.org/10.1073/pnas.1615922114.
[31] M.O. Adetutu, V. Ajayi, The impact of domestic and foreign R&D on agricultural productivity in sub-Saharan Africa, World Development. 125 (2020). https://ideas.repec.org/a/eee/wdevel/v125y2020ics0305750x19303389.html (accessed July 23, 2021).

[32] B. Gong, Agricultural productivity convergence in China, China Economic Review. 60 (2020). https://ideas.repec.org/a/eee/chieco/v60y2020ics1043951x20300201.html (accessed July 23, 2021).
[33] J. Gui, L. ZhaoHua, D. XiangZheng, Y. Jun, C. DongDong, L. WenQiang, An analysis of spatiotemporal patterns in Chinese agricultural productivity between 2004 and 2014., Ecological Indicators. 105 (2019) 591–600.
[34] Y. Nakano, E.F. Magezi, The impact of microcredit on agricultural technology adoption and productivity: Evidence from randomized control trial in Tanzania, World Development. 133 (2020). https://ideas.repec.org/a/eee/wdevel/v133y2020ics0305750x20301236.html (accessed July 23, 2021).
[35] S. Piya, A. Kiminami, H. Yagi, Sources of Agricultural Productivity Growth in South and Southeast Asia, Trends in Agricultural Economics. 4 (2011) 18–29. https://doi.org/10.3923/tae.2011.18.29.
[36] A.R. Anik, S. Rahman, J.R. Sarker, Agricultural productivity growth and the role of capital in south Asia (1980–2013), Sustainability. 9 (2017) 1–24. https://ideas.repec.org/a/gam/jsusta/v9y2017i3p470-d93654.html (accessed July 23, 2021).
[37] K. Kalirajan, The economic efficiency of farmers growing high-yielding irrigated rice in India, American Journal of Agricultural Economics. 63 (1981) 566–570. https://ideas.repec.org/a/oup/ajagec/v63y1981i3p566-570..html (accessed September 2, 2021).
[38] D.S. Sidhu, D. Byerlee, Technical Change and Wheat Productivity in Post-Green Revolution Punjab, Economic and Political Weekly. 26 (1991) A159–A166.
[39] K.K. Datta, P.K. Joshi, Economic efficiencies and land augmentation to increase agricultural production: A comparative analysis for investment priorities, Indian Journal of Agricultural Economics. 47 (1992) 468–476.
[40] M. Rosegrant, R.E. Evenson, Agricultural productivity growth in Pakistan and India: a comparative analysis, The Pakistan Development Review. 32 (1993) 433–451. https://econpapers.repec.org/article/pidjournl/v_3a32_3ay_3a1993_3ai_3a4_3ap_3a433-451.htm (accessed July 23, 2021).
[41] G.E. Battese, T.J. Coelli, A model for technical inefficiency effects in a stochastic frontier production function for panel data, Empirical Economics. 20 (1995) 325–332. https://doi.org/10.1007/BF01205442.
[42] R.E. Evenson, C. Pray, M.W. Rosegrant, Agricultural Research and Productivity Growth in India, Intl Food Policy Res Inst, 1998.
[43] K.R. Shanmugam, Technical efficiency of Rice grower in Bihar, Indian Journal of Applied Economics. 8 (2000) 377–389.
[44] R. Murgai, The Green Revolution and the productivity paradox: evidence from the Indian Punjab, Agricultural Economics. 25 (2001) 199–209. https://doi.org/10.1111/j.1574-0862.2001.tb00200.x.
[45] P. Kumar, A. Kumar, S. Mittal, Total factor productivity of crop sector in the Indo-Gangetic plain of India: sustainability issues revisited, Indian Economic Review. 39 (2004) 169–201. https://www.jstor.org/stable/29793810 (accessed July 23, 2021).
[46] T.J. Coelli, D.S.P. Rao, C.J. O'Donnell, G.E. Battese, An Introduction to Efficiency and Productivity Analysis, 2nd ed., Springer US, 2005. https://doi.org/10.1007/b136381.

[47] A. Tripathi, Total Factor Productivity Growth in Indian Agriculture, Journal of Global Economy. 6 (2010) 286–298.
[48] K. Emerick, Agricultural productivity and the sectoral reallocation of labor in rural India, Journal of Development Economics. 135 (2018) 488–503. https://ideas.repec.org/a/eee/deveco/v135y2018icp488-503.html (accessed July 23, 2021).
[49] K. Kalirajan, R.T. Shand, Sources of output growth in Indian agriculture, Indian Journal of Agricultural Economics. 52 (1997).
[50] L.R. Christensen, D.W. Jorgenson, L.J. Lau, Conjugate duality and the transcendental logarithmic function, Econometrica. 39 (1971) 255–256. https://www.sid.ir/en/journal/ViewPaper.aspx?ID=310005 (accessed September 2, 2021).
[51] F.M. Mari, H.D. Lohano, Measuring Production Function and Technical Efficiency of Onion, Tomato, and Chillies Farms in Sindh, Pakistan, The Pakistan Development Review. 46 (2007) 1053–1064. https://doi.org/10.30541/v46i4IIpp.1053-1064.
[52] G.E. Battese, T.J. Coelli, Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India, J Prod Anal. 3 (1992) 153–169. https://doi.org/10.1007/BF00158774.
[53] J. Jondrow, C.A. Knox Lovell, I.S. Materov, P. Schmidt, On the estimation of technical inefficiency in the stochastic frontier production function model, Journal of Econometrics. 19 (1982) 233–238. https://doi.org/10.1016/0304-4076(82)90004-5.
[54] K.P. Kalirajan, R.T. Shand, A generalized measure of technical efficiency, Applied Economics. 21 (1989) 25–34. https://doi.org/10.1080/772284229.
[55] S. Kumbhakar, H.-J. Wang, A.P. Horncastle, A Practitioner's Guide to Stochastic Frontier Analysis Using Stata, Cambridge University Press, 2015. https://econpapers.repec.org/bookchap/cupcbooks/9781107029514.htm (accessed September 2, 2021).
[56] W. Greene, Fixed and Random Effects in Stochastic Frontier Models, Journal of Productivity Analysis. 23 (2005) 7–32. https://www.jstor.org/stable/41770178 (accessed September 2, 2021).
[57] W. Greene, Maximum likelihood estimation of econometric frontier functions, Journal of Econometrics. 13 (1980) 27–56. https://econpapers.repec.org/article/eeeeconom/v_3a13_3ay_3a1980_3ai_3a1_3ap_3a27-56.htm (accessed September 2, 2021).
[58] V.P.S. Arora, Agricultural policies in India: retrospect and prospect, Agricultural Economics Research Review. 26 (2013). https://ideas.repec.org/a/ags/aerrae/162144.html (accessed January 20, 2022).
[59] M. Kniivilä, Industrial development and economic growth: implications for poverty reduction and income inequality, in: Industrial Development for the 21st Century: Sustainable Development Perspectives., United Nations, New York, 2007.
[60] K.P. Kalirajan, G. Mythili, U. Sankar, Accelerating growth through globalization of Indian agriculture, Macmillan India, Delhi, 2001.
[61] P.K. Joshi, A. Gulati, P.S. Birthal, L. Tewari, eds., Agriculture Diversification in South Asia: Patterns, Determinants, and Policy Implications, 2003. https://doi.org/10.22004/ag.econ.16215.

[62] K.K. Kakarlapudi, Agricultural Growth Deceleration In India: An Enquiry Into Possible Explanations, Journal of Regional Development and Planning. 1 (2012) 25–40. https://ideas.repec.org/a/ris/jrdpin/0003.html (accessed September 1, 2021).
[63] R. Chand, India's national agricultural policy: a critique, Indian Journal of Agricultural Economics. 64 (2004) 164–87. https://scholar.google.com/scholar_lookup?title=India%E2%80%99s+national+agricultural+policy%3A+a+critique&author=R.+Chand&publication_year=2004 (accessed January 20, 2022).
[64] R. Chand, P. Kumar, S. Kumar, Total factor productivity and contribution of research investment to agricultural growth in India, National Centre for Agricultural Economics and Policy Research, New Delhi, 2011.
[65] OECD/ICRIER, Agricultural Policies in India: OECD Food and Agricultural Reviews, OECD Publishing, Paris, 2018.
[66] R. Jain, R. Chand, A. Singh, Total factor productivity growth in Indian crop sector, Indian Journal of Agricultural Economics. 74 (2017) 535–554.
[67] R. Mahapatra, J. Choubey, Victim of its success, Down To Earth. (2013). https://www.downtoearth.org.in/coverage/victim-of-its-success-40443.
[68] V.K. Das, Agricultural productivity growth in India: an analysis accounting for different land types, The Journal of Developing Areas. 50 (2016) 349–366. https://www.jstor.org/stable/24737407 (accessed January 22, 2022).
[69] A. Ortiz-Bobea, T.R. Ault, C.M. Carrillo, R.G. Chambers, D.B. Lobell, Anthropogenic climate change has slowed global agricultural productivity growth, Nat. Clim. Chang. 11 (2021) 306–312. https://doi.org/10.1038/s41558-021-01000-1.
[70] S. Ghosh, Indian Economy, PHI Learning Private Limited, Delhi, 2022.
[71] FAO, Foresight natural farming in Andhra Pradesh by 2050, Agroecology Knowledge Hub, Food and Agriculture Organization. (2020). https://www.fao.org/agroecology/slideshow/news-article/en/c/1259916/.
[72] N. Rada, D. Schimmelpfennig, Propellers of agricultural productivity in India, US Department of Agriculture, 2015. https://papers.ssrn.com/abstract=2715084 (accessed January 22, 2022).
[73] M.J. Bhende, K. Kalirajan, Technical Efficiency of Major Food and Cash Crops in Karnataka (India), Indian Journal of Agricultural Economics. 62 (2007). https://econpapers.repec.org/article/agsinijae/204514.htm (accessed October 11, 2021).
[74] E. Kannan, Total Factor Productivity Growth and Its Determinants in Karnataka Agriculture, Institute for Social and Economic Change, Bangalore, 2011. https://ideas.repec.org/p/sch/wpaper/265.html (accessed October 11, 2021).
[75] C. Kumar, Farmer suicides in Karnataka at 25-year low due to good rain, The Times of India. (2021).
[76] A. Borah, Monsoon-friendly Assam reeling under drought, Down To Earth. (2006). https://www.downtoearth.org.in/coverage/monsoonfriendly-assam-reeling-under-drought-8413.
[77] D. Sabasi, C.R. Shumway, eds., Technical change, efficiency, and total factor productivity in US agriculture, in: Minneapolis, 2014. https://doi.org/10.22004/ag.econ.170225.

[78] U. Lall, Punjab: a tale of prosperity and decline, State of the Planet. (2009). https://news.climate.columbia.edu/2009/07/28/punjab-a-tale-of-prosperity-and-decline/ (accessed January 23, 2022).
[79] R. Chand, Emerging crisis in Punjab agriculture: severity and options for future, Economic and Political Weekly. 34 (1999) A2–A10. https://www.jstor.org/stable/4407788 (accessed January 23, 2022).
[80] A. Hoda, P. Rajkhowa, A. Gulati, Unleashing Bihar's agriculture potentia: sources and drivers of agriculture growth, ICRIER, New Delhi, 2017. https://www.econstor.eu/handle/10419/176363 (accessed January 23, 2022).
[81] C.J. O'Donnell, Measuring and decomposing agricultural productivity and profitability change, Australian Journal of Agricultural and Resource Economics. 54 (2010) 527–560. https://doi.org/10.1111/j.1467-8489.2010.00512.x.
[82] N.B. Chhetri, W.E. Easterling, A. Terando, L. Mearns, Modeling path dependence in agricultural adaptation to climate variability and Change, Annals of the Association of American Geographers. 100 (2010) 894–907. https://doi.org/10.1080/00045608.2010.500547.

## Figures

Figure 1 (Decomposition of output growth (q) against input use (x))

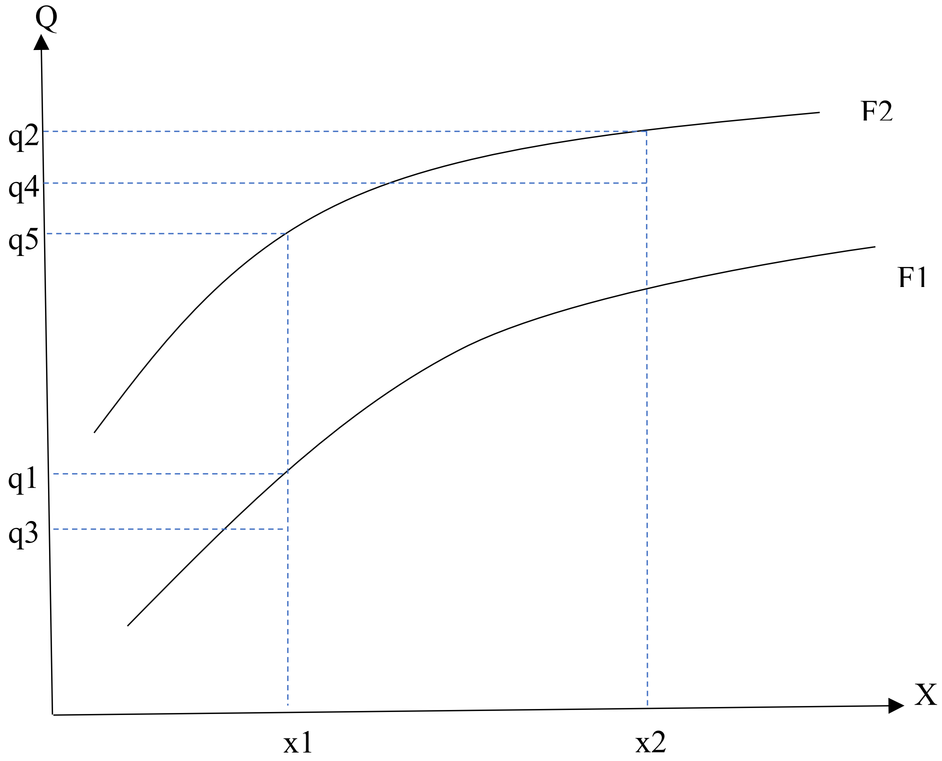



Figure 2.1 (Mean technical efficiency over the year)

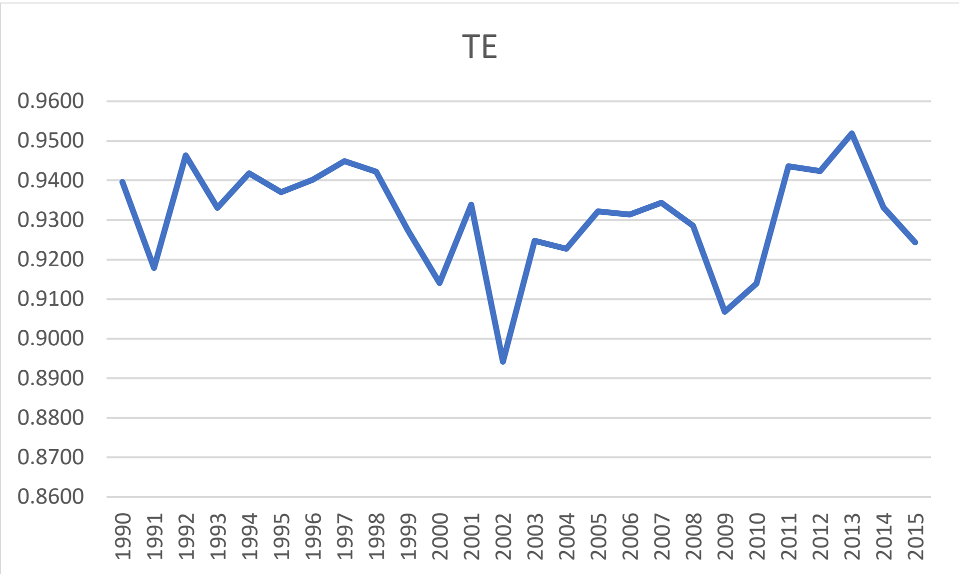


Figure 2.2 (Mean technical efficiency across the states)

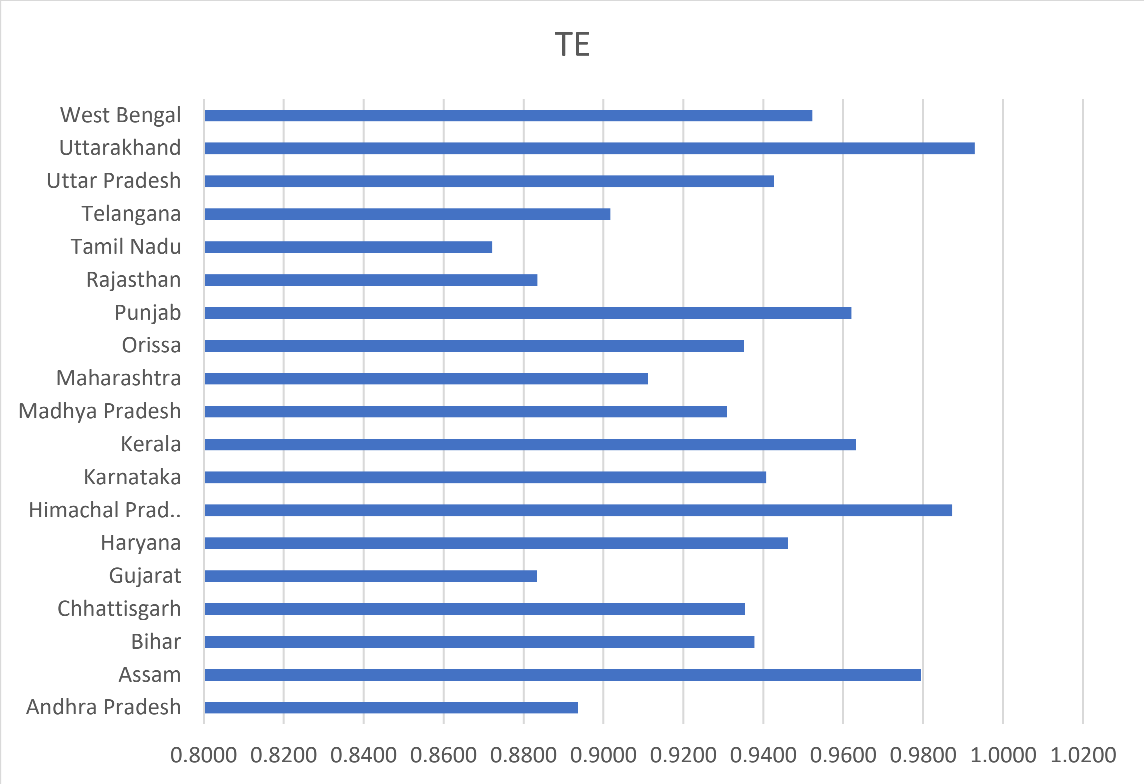



Figure 3.1 (Mean technical progress over the year)

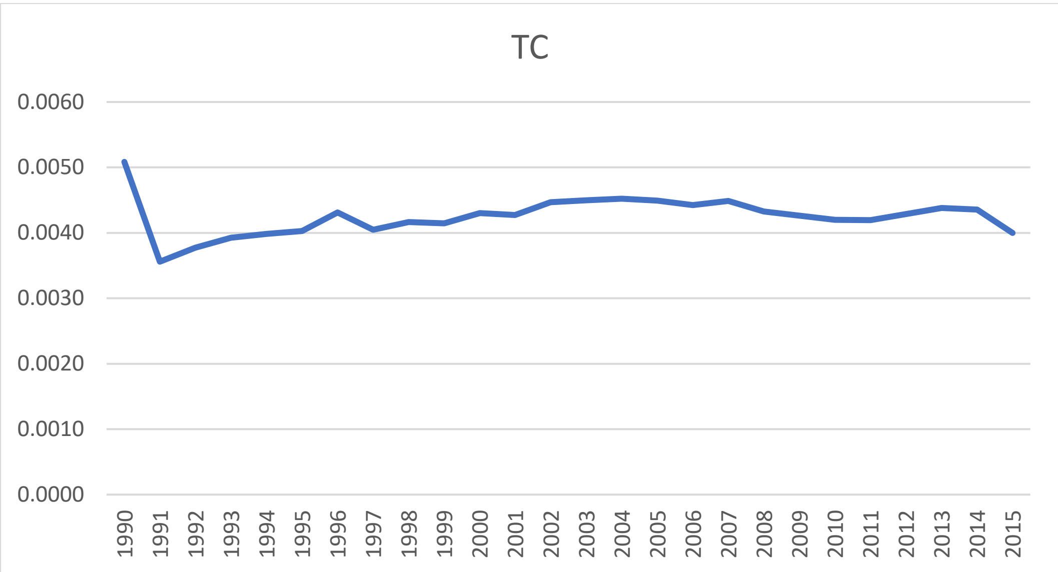


Figure 3.2 (Mean technical efficiency change over the year)

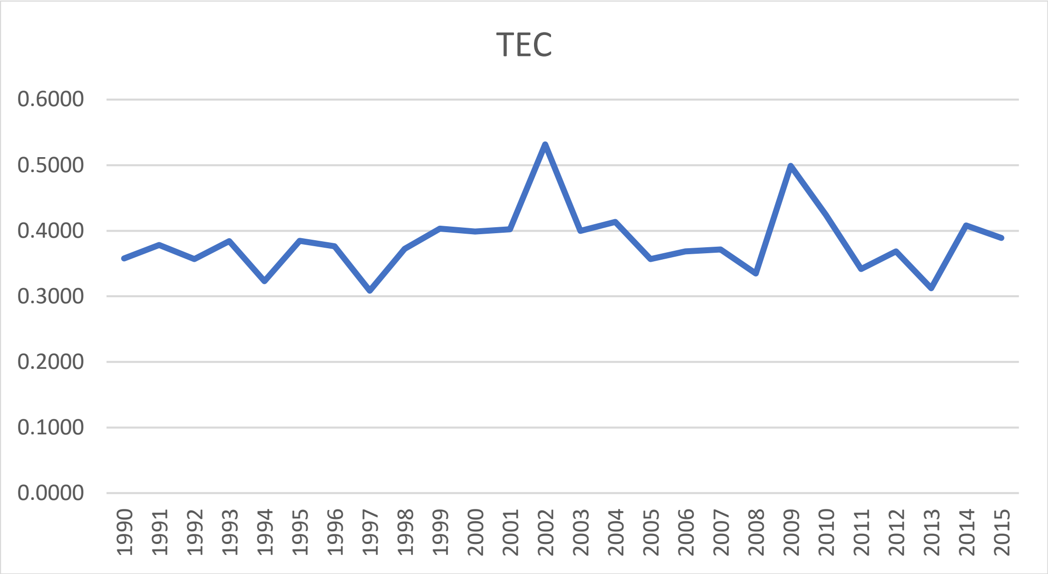



Figure 3.3 (Mean scale efficiency over the year)

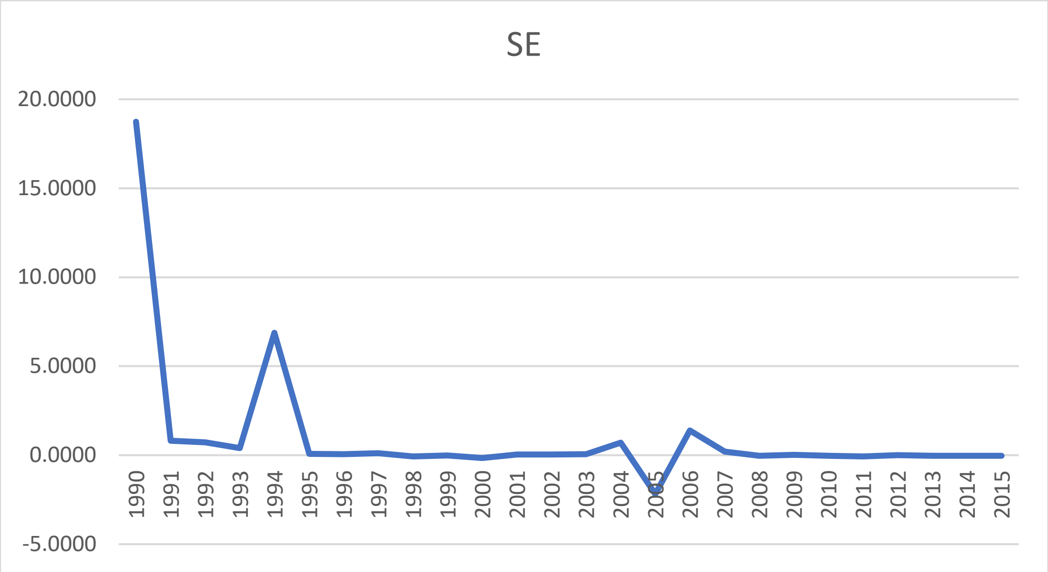


Figure 3.4 (Mean total factor productivity growth over the year)

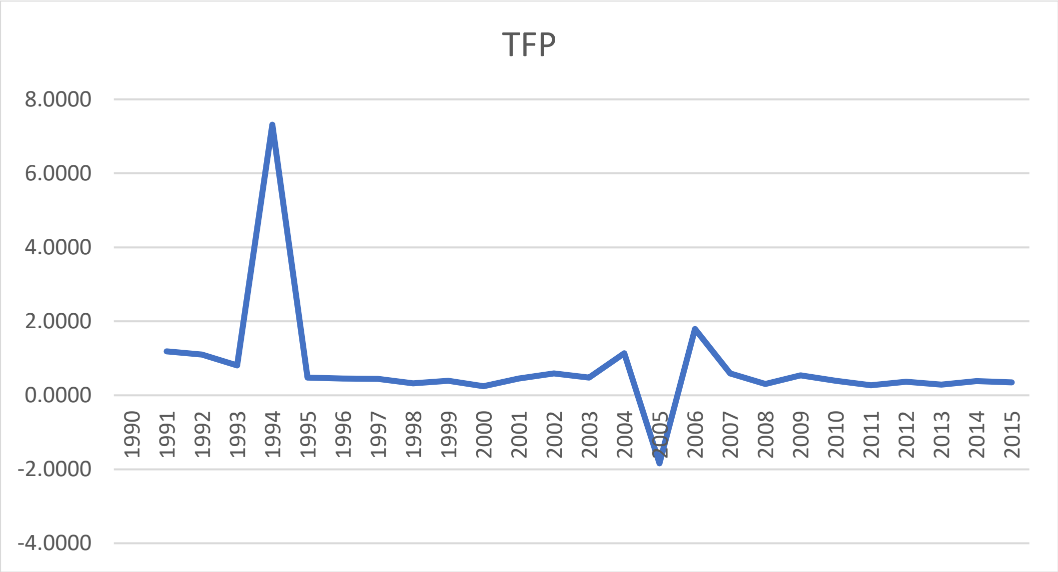



Figure 4.1 (Mean technical progress across the states)

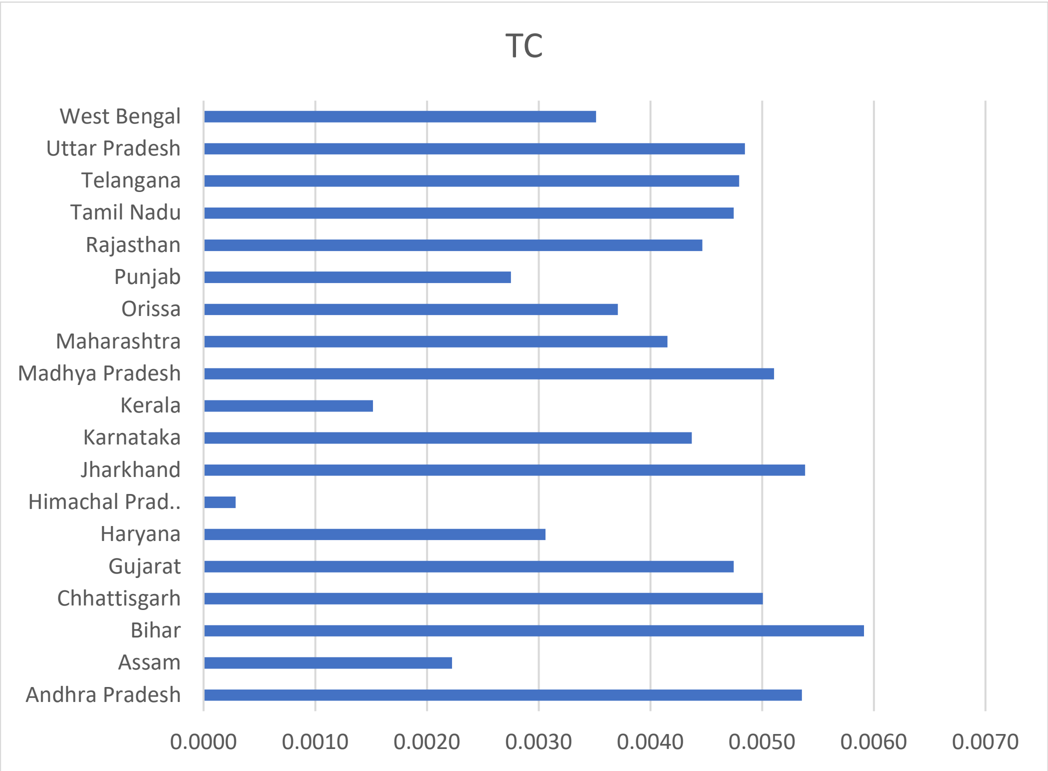


Figure 4.2 (Mean technical efficacy change across the states)

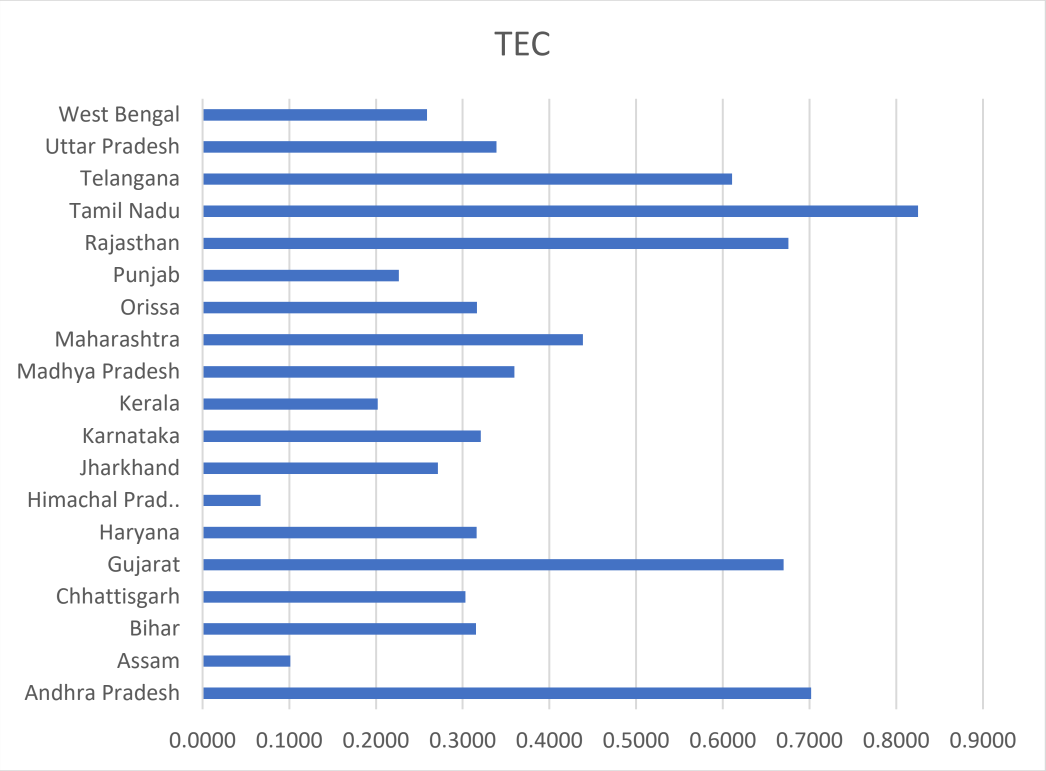



Figure 4.3 (Mean scale efficiency across the states)

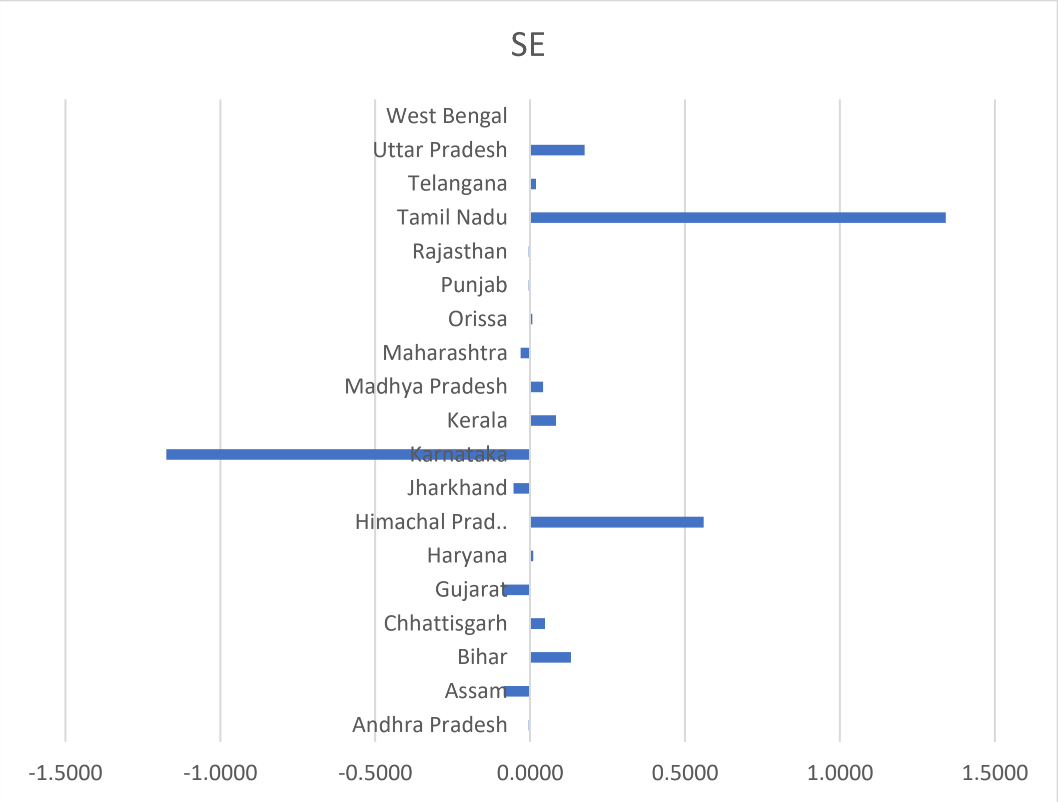
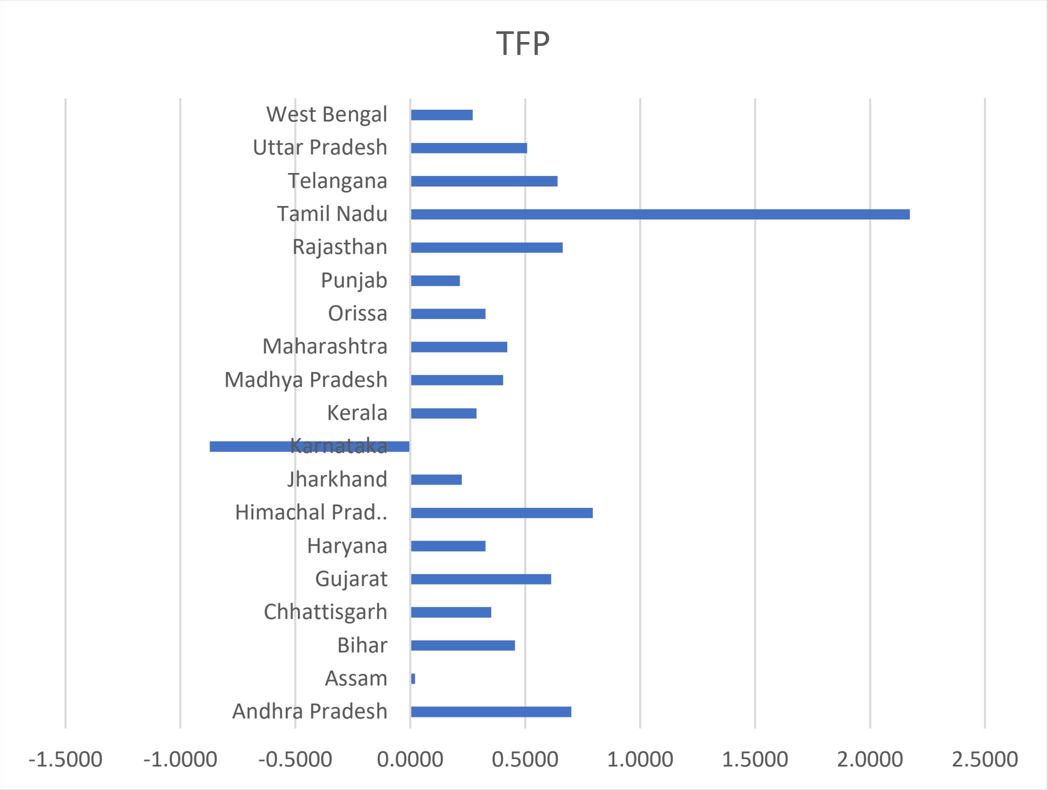


Figure 4.4 (Mean total factor productivity growth across the states)



## Tables

Table 1 (Estimation of panel frontier model)

| Variable | Coefficient | Standard error | z | Prob >\|z\| |
|---|---|---|---|---|
| ln A | 0.5103 | 1.6995 | 0.3000 | 0.7640 |
| ln L | 8.1527 | 1.0830 | -7.5300 | 0.0000 |
| ln K | 3.7187 | 0.4523 | -8.2200 | 0.0000 |
| ln W | 6.6165 | 1.0181 | 6.5000 | 0.0000 |
| ln $A^2$ | 0.4533 | 0.0590 | 7.6800 | 0.0000 |
| ln $L^2$ | 0.0467 | 0.0255 | 1.8300 | 0.0670 |
| ln $K^2$ | 0.0076 | 0.0051 | 1.4700 | 0.1410 |
| ln $W^2$ | 0.0719 | 0.0132 | 5.4300 | 0.0000 |
| ln A. ln L | 0.0567 | 0.0335 | -1.6900 | 0.0900 |
| ln A. ln K | 0.0512 | 0.0136 | 3.7800 | 0.0000 |
| ln A. ln W | 0.0647 | 0.0208 | -3.1100 | 0.0020 |
| ln L. ln K | 0.0219 | 0.0086 | -2.5500 | 0.0110 |
| ln L. ln W | 0.0058 | 0.0157 | 0.3700 | 0.7110 |
| ln K. ln W | 0.0177 | 0.0058 | -3.0700 | 0.0020 |
| t | 0.0098 | 0.0020 | 5.0200 | 0.0000 |
| $t^2$ | 0.0000 | (omitted) | | |
| t. ln A | 0.0002 | 0.0008 | -0.2600 | 0.7980 |
| t. ln L | 0.0041 | 0.0005 | 7.5600 | 0.0000 |
| t. ln K | 0.0018 | 0.0002 | 8.2400 | 0.0000 |
| t. ln W | 0.0033 | 0.0005 | -6.5300 | 0.0000 |
| ln $Z_1$ | 41.8115 | 1.9988 | 20.9200 | 0.0000 |
| ln $Z_2$ | 3.0458 | 0.3179 | -9.5800 | 0.0000 |
| ln $Z_3$ | 0.3954 | 0.4199 | 0.9400 | 0.3460 |
| ln $Z_4$ | 0.9330 | 0.2802 | 3.3300 | 0.0010 |
| $\sigma_u$ | 59.0982 | 2.7759 | -21.2900 | 0.0000 |
| $\sigma_v$ | 5.3409 | 0.0252 | -212.3300 | 0.0000 |
| Observations | 11062 | | | |
| Log likelihood | 10907.4870 | | | |
| $\sigma_v^2$ (t statistics) | 0.004 (39.76) | | | |
| Wald $chi^2$ (497) | 248013.6800 | | | |
| Prob > $chi^2$ | 0.0000 | | | |
| District dummies excluded | | | | |

Numerically formatted numbers to four decimal places

Table 2 (Descriptive statistics of decomposed components)

| Var | Observations | Mean | Standard deviation | Min | Max |
|---|---|---|---|---|---|
| TC | 10927 | 0.004 | 0.002 | -0.003 | 0.012 |
| TEC | 11299 | 0.384 | 0.281 | 0.000 | 6.011 |
| SE | 13777 | 0.293 | 22.503 | -1035.151 | 1494.846 |
| TFP | 10798 | 0.688 | 22.635 | -1034.844 | 1494.871 |

Numerically formatted numbers to three decimal places

Table 3 (Year-wise and state-wise mean technical efficiency)

| | TE | Mean | Standard deviation | Frequency |
|---|---|---|---|---|
| Year-wise | 1990 | 0.9396 | 0.0454 | 295 |
| | 1991 | 0.9179 | 0.0755 | 298 |
| | 1992 | 0.9463 | 0.0339 | 341 |
| | 1993 | 0.9331 | 0.0789 | 370 |
| | 1994 | 0.9418 | 0.0529 | 356 |
| | 1995 | 0.9371 | 0.0522 | 389 |
| | 1996 | 0.9402 | 0.0445 | 371 |
| | 1997 | 0.9448 | 0.0459 | 420 |
| | 1998 | 0.9422 | 0.0455 | 447 |
| | 1999 | 0.9275 | 0.0722 | 452 |
| | 2000 | 0.9141 | 0.0821 | 464 |
| | 2001 | 0.9339 | 0.0452 | 463 |
| | 2002 | 0.8942 | 0.0866 | 465 |
| | 2003 | 0.9248 | 0.0751 | 461 |
| | 2004 | 0.9227 | 0.0558 | 465 |
| | 2005 | 0.9322 | 0.0543 | 466 |
| | 2006 | 0.9314 | 0.0465 | 470 |
| | 2007 | 0.9344 | 0.0534 | 471 |
| | 2008 | 0.9285 | 0.0563 | 473 |
| | 2009 | 0.9068 | 0.0747 | 473 |
| | 2010 | 0.9139 | 0.0815 | 450 |
| | 2011 | 0.9436 | 0.0520 | 450 |
| | 2012 | 0.9424 | 0.0553 | 450 |
| | 2013 | 0.9519 | 0.0449 | 450 |
| | 2014 | 0.9331 | 0.0615 | 472 |
| | 2015 | 0.9243 | 0.0732 | 380 |
| | Total | 0.9304 | 0.0628 | 11062 |
| State-wise | Andhra Pradesh | 0.8936 | 0.0644 | 337 |
| | Assam | 0.9795 | 0.0094 | 509 |
| | Bihar | 0.9378 | 0.0346 | 804 |
| | Chhattisgarh | 0.9354 | 0.0577 | 318 |
| | Gujarat | 0.8834 | 0.0930 | 457 |
| | Haryana | 0.9461 | 0.0267 | 481 |
| | Himachal Pradesh | 0.9873 | 0.0175 | 241 |
| | Karnataka | 0.9407 | 0.0496 | 644 |
| | Kerala | 0.9632 | 0.0163 | 358 |
| | Madhya Pradesh | 0.9309 | 0.0446 | 1151 |
| | Maharashtra | 0.9111 | 0.0742 | 760 |
| | Orissa | 0.9351 | 0.0500 | 695 |
| | Punjab | 0.9621 | 0.0149 | 440 |
| | Rajasthan | 0.8835 | 0.1019 | 808 |
| | Tamil Nadu | 0.8722 | 0.0951 | 632 |

| | | | |
|---|---|---|---|
| Telangana | 0.9018 | 0.0478 | 226 |
| Uttar Pradesh | 0.9427 | 0.0227 | 1603 |
| Uttarakhand | 0.9928 | 0.0082 | 184 |
| West Bengal | 0.9523 | 0.0263 | 414 |
| Total | 0.9304 | 0.0628 | 11062 |

Numerically formatted numbers to four decimal places

Table 4.1 (Year-wise decomposition of TFP growth)

| | TC | | TEC | | SE | | TFP | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| 1991 | 0.0036 | 0.0016 | 0.3781 | 0.3209 | 0.8103 | 12.7868 | 1.1921 | 12.8332 |
| 1992 | 0.0038 | 0.0016 | 0.3570 | 0.2303 | 0.7293 | 12.5141 | 1.0984 | 12.6336 |
| 1993 | 0.0039 | 0.0016 | 0.3844 | 0.2778 | 0.4018 | 12.2525 | 0.8093 | 12.3346 |
| 1994 | 0.0040 | 0.0016 | 0.3229 | 0.2208 | 6.8813 | 97.2490 | 7.3175 | 97.8874 |
| 1995 | 0.0040 | 0.0017 | 0.3846 | 0.2876 | 0.0790 | 1.1459 | 0.4757 | 1.1420 |
| 1996 | 0.0043 | 0.0016 | 0.3765 | 0.2448 | 0.0584 | 4.4837 | 0.4567 | 4.5025 |
| 1997 | 0.0041 | 0.0018 | 0.3086 | 0.2183 | 0.1151 | 2.3750 | 0.4468 | 2.4296 |
| 1998 | 0.0042 | 0.0016 | 0.3725 | 0.2636 | -0.0618 | 0.8861 | 0.3233 | 0.9225 |
| 1999 | 0.0041 | 0.0017 | 0.4030 | 0.3041 | -0.0077 | 1.1745 | 0.3948 | 1.2162 |
| 2000 | 0.0043 | 0.0016 | 0.3988 | 0.2848 | -0.1562 | 2.6172 | 0.2500 | 2.6679 |
| 2001 | 0.0043 | 0.0017 | 0.4022 | 0.2721 | 0.0414 | 0.5776 | 0.4560 | 0.6444 |
| 2002 | 0.0045 | 0.0017 | 0.5317 | 0.5083 | 0.0321 | 1.2194 | 0.5905 | 1.3140 |
| 2003 | 0.0045 | 0.0017 | 0.3998 | 0.2845 | 0.0651 | 1.8849 | 0.4804 | 1.9221 |
| 2004 | 0.0045 | 0.0017 | 0.4135 | 0.2866 | 0.7005 | 21.9747 | 1.1323 | 22.0903 |
| 2005 | 0.0045 | 0.0017 | 0.3567 | 0.2178 | -2.1848 | 46.7231 | -1.8391 | 46.9658 |
| 2006 | 0.0044 | 0.0017 | 0.3687 | 0.2189 | 1.3959 | 33.0848 | 1.7928 | 33.3276 |
| 2007 | 0.0045 | 0.0018 | 0.3712 | 0.2286 | 0.2027 | 4.2926 | 0.5879 | 4.3251 |
| 2008 | 0.0043 | 0.0017 | 0.3346 | 0.2043 | -0.0357 | 0.7659 | 0.3060 | 0.7998 |
| 2009 | 0.0043 | 0.0018 | 0.4989 | 0.3008 | 0.0276 | 0.3842 | 0.5399 | 0.4909 |
| 2010 | 0.0042 | 0.0018 | 0.4240 | 0.2342 | -0.0390 | 0.9041 | 0.3910 | 0.9385 |
| 2011 | 0.0042 | 0.0018 | 0.3416 | 0.2407 | -0.0606 | 0.7745 | 0.2754 | 0.8204 |
| 2012 | 0.0043 | 0.0017 | 0.3686 | 0.2865 | 0.0053 | 0.0890 | 0.3671 | 0.2932 |
| 2013 | 0.0044 | 0.0018 | 0.3126 | 0.2581 | -0.0285 | 0.6981 | 0.2873 | 0.7548 |
| 2014 | 0.0044 | 0.0018 | 0.4082 | 0.3043 | -0.0241 | 0.7036 | 0.3836 | 0.7730 |
| 2015 | 0.0040 | 0.0018 | 0.3891 | 0.2739 | -0.0344 | 0.2270 | 0.3483 | 0.3701 |
| Total | 0.0042 | 0.0017 | 0.3843 | 0.2812 | 0.2928 | 22.4973 | 0.6881 | 22.6323 |

Numerically formatted numbers to four decimal place

Table 4.2 (State-wise decomposition of TFP growth)

| | TC | | TEC | | SE | | TFP | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation | Mean | Standard deviation |
| Andhra Pradesh | 0.0054 | 0.0006 | 0.7019 | 0.2809 | -0.0052 | 0.1226 | 0.7000 | 0.3071 |
| Assam | 0.0022 | 0.0020 | 0.1011 | 0.0320 | -0.0858 | 2.4363 | 0.0200 | 2.4376 |
| Bihar | 0.0059 | 0.0010 | 0.3152 | 0.1044 | 0.1306 | 3.0011 | 0.4558 | 3.0028 |
| Chhattisgarh | 0.0050 | 0.0009 | 0.3030 | 0.1145 | 0.0484 | 0.5126 | 0.3520 | 0.5370 |
| Gujarat | 0.0047 | 0.0010 | 0.6700 | 0.2715 | -0.0876 | 1.7619 | 0.6122 | 1.7781 |
| Haryana | 0.0031 | 0.0007 | 0.3162 | 0.1270 | 0.0100 | 0.1236 | 0.3267 | 0.1718 |
| Himachal Pradesh | 0.0003 | 0.0015 | 0.0671 | 0.1018 | 0.5598 | 19.9874 | 0.7939 | 21.0333 |
| Jharkhand | 0.0054 | 0.0018 | 0.2713 | 0.0787 | -0.0535 | 1.0346 | 0.2239 | 1.0408 |
| Karnataka | 0.0044 | 0.0013 | 0.3210 | 0.1896 | -1.1739 | 45.8851 | -0.8729 | 46.1482 |
| Kerala | 0.0015 | 0.0014 | 0.2021 | 0.0853 | 0.0837 | 1.5710 | 0.2879 | 1.5744 |
| Madhya Pradesh | 0.0051 | 0.0011 | 0.3596 | 0.1306 | 0.0420 | 1.9742 | 0.4038 | 1.9761 |
| Maharashtra | 0.0042 | 0.0012 | 0.4385 | 0.1832 | -0.0309 | 0.5176 | 0.4214 | 0.5678 |
| Orissa | 0.0037 | 0.0012 | 0.3166 | 0.0998 | 0.0068 | 0.1880 | 0.3267 | 0.2140 |
| Punjab | 0.0028 | 0.0014 | 0.2263 | 0.0982 | -0.0056 | 0.0400 | 0.2153 | 0.0961 |
| Rajasthan | 0.0045 | 0.0012 | 0.6755 | 0.5026 | -0.0055 | 0.4123 | 0.6624 | 0.6285 |
| Tamil Nadu | 0.0047 | 0.0012 | 0.8251 | 0.3729 | 1.3411 | 30.0929 | 2.1738 | 30.1106 |
| Telangana | 0.0048 | 0.0009 | 0.6107 | 0.1640 | 0.0190 | 0.1755 | 0.6409 | 0.2380 |
| Uttar Pradesh | 0.0048 | 0.0010 | 0.3390 | 0.1295 | 0.1757 | 5.8102 | 0.5078 | 5.8239 |
| Uttarakhand | 0.0023 | 0.0020 | 0.0358 | 0.0567 | 14.9447 | 140.7415 | 14.9844 | 140.7389 |
| West Bengal | 0.0035 | 0.0013 | 0.2588 | 0.1080 | 0.0000 | 0.0495 | 0.2716 | 0.1100 |
| Total | 0.0042 | 0.0017 | 0.3843 | 0.2812 | 0.2928 | 22.4973 | 0.6881 | 22.6323 |

Numerically formatted numbers to four decimal places