Labour productivity in India: An analysis of regional and sectoral sources

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Abstract

This paper examines sources and determinants of labour productivity growth in India on two dimensions. First, we consider worker reallocation across states and industries in India. We decompose workers' movement from low productivity states/industries to high productivity ones using a shift-share analysis and find that the overall improvement in national labour productivity is primarily coming from within industry productivity growth, whereas 1/5th of total labour productivity growth in the 2004-2019 period is achieved from labour reallocation effects. Second, we examine the determinants of labour productivity across states (provinces) in India. Our panel econometric results using provincial-level data show that the labour productivity is mainly driven by capital stocks, improvement in health, urbanization, infrastructure and rise in manufacturing share whereas the impact of education is found to be negligible.

JEL Classification: O10, O40, O47, R11

Keywords: Labour productivity, shift-share analysis, labour reallocation, Indian States, determinants of labour productivity.

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1. Introduction

The importance of productivity growth for sustaining long-run economic growth is widely agreed upon among economists, and Krugman (1997)'s famous statement "productivity isn't everything, but in the long run it is almost everything" rightly reflects it. Labour productivity, or the amount of output an average worker produces (or the amount of output produced per an average working hour), is the most commonly used measure of partial productivity.[*] Growth in the average output per worker or worker hour indicates the improvements in the efficiency of workers in producing output, be it using better technologies, through innovation, acquiring better skills and training, or better competencies. Therefore, several factors, such as education and skill of workers, better health condition of the workers, capital equipment available to assist workers in the production process, management competencies, innovation, investment in modern technologies (e.g., information technologies), intangibles, etc., are all important drivers of worker productivity. Improving productivity growth at the macro-level, if not happening at the cost of employment, also indicates improvement in welfare, as it reflects more output per worker - in other words, more output to consume.[†] However, productivity growth is often accused of an achievement at the cost of job creation. Although empirical evidence supports this claim, it is only a short-term phenomenon (Galí, 1999; Walsh, 2004), re-enforcing Krugman (1997)'s observation of how productivity is important for long-term welfare.

At the firm level, there are several factors that drive productivity growth (Syverson, 2011). However, from a welfare perspective, productivity growth at the aggregate level gains relevance, and aggregate productivity can be improved in two ways. The first is the improvement in productivity in individual industries - technological changes often take place at the level of

[*] Productivity can be measured either in partial terms - as output per unit of a given factor input - or as total factor productivity (TFP). In the latter case, one takes out the contribution of all factor inputs, such as labour, capital, and material, to isolate the contribution of disembodied technology or TFP. The TFP is considered not only a comprehensive measure of efficiency but also an indicator of welfare (See Syverson, 201; Basu and Fernald, 2002; Basu et al., 2014; Erumban and van Ark, 2017). In this study, we focus on worker reallocation across states and sectors using labour productivity measures. Extending such analysis to TFP would require more comprehensive data on other factor inputs, particularly capital input, at the state-industry level.

[†] Furthermore, as suggested by Baumol cost disease (Baumol and Bowen, 1966), technological change and productivity growth in some sectors can lead to wage rises in other sectors as well, which are not witnessing productivity growth. The rise in overall wages and incomes and increases in output helps improve welfare measured in per capita income.

industries. The second is the movement of workers from low productivity industries to high productivity ones so that the average productivity of the aggregate economy will improve.[‡] This process is at the heart of the structural change hypothesis (Fisher, 1939; Clark, 1940; Lewis, 1954; Kuznets, 1966; Chenery and Syrquin, 1975). In the famous Lewis (1954) two-sector model, the economic development process entails worker movement from the traditional agricultural sector to the modern industrial sector. The modern industrial sector is featured by higher productivity and, therefore, generates higher income and welfare. Further development in the literature (Kuznets, 1966) introduced a three-sector model, where workers will further move to services sectors as the level of income increases. Many studies have tested this hypothesis in the past and proven to be a feature of post-war growth dynamics in many of today's advanced economies (Denison, 1967; Maddison, 1987; Jorgenson and Timmer, 2011). More recently, the literature on structural change moved to a broader approach, defining structural change as a continuing process where resources move from low productivity sectors to high productivity sectors (Lin, 2011; McMillan and Rodrik, 2011; Naude et al., 2015; Szirmai, 2013; de Vries et al., 2012; Erumban and Das, 2019).

This paper analyzes the sources and determinants of labour productivity in India. Although productivity research in India is quite extensive, they primarily focus on the manufacturing sector and is confined to the national economy. In contrast, analysis beyond the manufacturing sector and differences across states is seldom available.[§] However, growth in and levels of labour productivity and per capita income – two highly interrelated concepts that have implications for welfare - are not uniform across states in India.[**] In this context, the objective of this paper is two-fold. First,

[‡] Several firm level studies also consider the resource reallocation hypothesis, that contributes to aggregate productivity growth (e.g., Melitz, 2003; Asplund and Nocke, 2006). In such models markets share shifts to more productive firms from less productive ones, either among exiting firms or through the entry (or exit) of new (old) firms. Since our study uses industry level data, we do not make any distinction between whether the worker movements are result of shifts among incumbent firms or through the entry of new firms and exit of the old ones.

[§] Some notable exceptions are Bhattacharya et al. (2018) and Veeramani and Goldar (2005) but are also confined to specific sectors of the economy.

[**] It may be noted that the regional disparities in India are not specific to labour productivity. Large disparities are also persistent in per capita income and other social indicators. Given that labour productivity implies more output per worker, its correlation with per capita income is quite high. The main difference between labour productivity and per capita income growth is the growth in work force participation rate. Therefore, one of the potential factors explaining variation in income growth among Indian states could be the variation in labour productivity.

taking the broad perspective on structural change, we examine the industry and worker reallocation sources of aggregate national labour productivity growth on two dimensions, using a shift-share analysis. The first dimension is the impact of worker movement across industries within the Indian states on the aggregate labour productivity for each state. The second dimension is the worker reallocation across states in India and its impact on aggregate national labour productivity growth. Here the hypothesis is that when workers move to more productive locations, national productivity will improve. Combining these two, we quantify the state-industry worker reallocation effects on aggregate productivity growth in India, which provides insight into whether workers are moving to states and industries which are more productive. While we do not intend to explain the factors that drive these reallocations, we try to quantify the magnitude of the impact of these reallocations on aggregate productivity growth.

The second objective is to understand the determinants of labour productivity across states in India. We identify a set of factors from the existing literature that can impact productivity and examine the role of those factors in explaining changes in productivity in Indian states using a panel econometric analysis. We delve deeply into understanding the factors that drive productivity differences across states in India, using measures of aggregate state-specific labour productivity and several explanatory variables identified by the literature. This is important from the perspective of between-state worker reallocation and to capture the large disparity between Indian states in terms of levels and growth rates of per capita income and labour productivity. It is also known that Indian states differ substantially in terms of education, health, environment, and working conditions, among many others, which are important ingredients to improving worker quality and labour productivity. Similarly, the level of private investments, foreign direct investment (FDI), and ease of doing business, which all rely on the all-out efforts shown by the state governments, could play an important role in determining a state's productivity. Due to federal structure of India, where different states are ruled by difference political parties in a democratic setting, the policy structure also varies across states.

Under this milieu, it is important to study the determinants of labour productivity across states. Such analysis will insights into the locational choices of industries, distribution of FDI, and state-wise variation in economic growth, which are the important factors to ensure equitable growth and reduce poverty. Thus, our study examines two important issues related to productivity growth in India, viz. (i) quantifying within and across industry-state contributions to national to labour productivity growth and (ii) the determinants of state-level labour productivity growth.

The paper is organized into six sections. After the introduction in Section 1, we discuss the review of literature in Section 2. Overall conditions of state economy have been discussed in Section 3. Section 4 deals with methodology adopted in the study and sources and periodicity of data collected for the study. Econometric results are discussed in Section 5. Finally, conclusion drawn from the study is discussed in Section 6.

2. Literature Review: determinants of productivity

Studies have emphasised the importance of productivity growth in explaining the competitiveness in export and differences in per capita income across countries. In this section, we discuss the literature on total factor productivity (TFP) and labour productivity in India. The literature on TFP in India's organized manufacturing sector since the economic liberalization policies were initiated in the 1990s is quite extensive (Goldar 1986, Ahluwalia 1985, Ahluwalia, 1991; Balakrishnan and Pushpangadan. 1994; Dholakia and Dholakia, 1994; Rao, 1996; Goldar, 2002). They have mostly dealt with the issue of measurement of manufacturing sector TPF growth at the national level. Although rare in number, some studies also considered productivity in the aggregate economy, beyond the organized manufacturing sector, but within the traditional three-sector model framework, such as Bosworth and Collins (2008). More recently, since the onset of the India KLEMS database, many studies have extended the analysis of productivity in India to more sectors of the economy beyond the three broad sectors (Goldar et al., 2017; Erumban et al., 2019). While these studies are generally conducted using data for the national economy, there are some studies at the regional level also (Mitra, et al., 2002; Ray, 2002; Trivedi, 2004; Veermani and Goldar, 2005; Acharya et al., 2009; Trivedi et al., 2011; Deb and Ray, 2014). These studies have tried to examine the disparities across states in respect of TFP. Different studies have ascribed these disparities to different factors, such as information and communication technology (ICT) infrastructure (Mitra, et al., 2002), financial development (Acharya et al., 2009), and institutional quality as well as investment climate (Veermani and Goldar, 2005). Some studies have pointed out that the regional disparities in India, in fact, have widened after the liberal market economic reforms.

For labour productivity, various cross country studies have looked into determinants of labour productivity at the regional level and emphasize on the role of health, education, infrastructure, urbanization and financial depth. Carlino and Voith (1992) find that education, public infrastructure, and percentage of urbanized population have a statistically significant positive influence in explaining differences in state labour productivity across US states. Smoluk and Andrews (2005) for US economy find that labour productivity is positively related to both the percentage of a state's population with a bachelor's degree or higher and the population density of a state, and negatively related to tax burden. Belorgey et al (2006) in a cross-country analysis of 77 countries found that that human capital (measured by gross school enrollment in primary and tertiary education) was positively significant as a determinant of labour productivity. Chansarn (2010) showed that mean years of schooling was statistically significant in explaining labour productivity. Bloom et al (2003) found health had a significant positive effect on labour productivity. Rivera and Currais (2013) also found that health and education had a significant impact on labour productivity.

There are various global studies that considered the factors determining regional or provincial differences in productivity. These studies generally tend to conclude that education and human capital, infrastructure, health, urbanization, population density, and tax rates are important determinants of regional labour productivity. Better educated workers increase the labour productivity by increasing the effective input, efficiently allocating inputs across production process, introducing new technology and promoting R&D (Welar, 1970; Nelson and Phelps, 1996; Corvers, 1997). Carlino and Voith (1992) found that education, along with public infrastructure and urbanization had a positive and significant effect in explaining differences in state labour productivity in the USA. Smoluk and Andrews (2005) also find a positive effect of education and population density on labour productivity. Good health is associated with reduced worker incapacity, lower days off due to illness, and higher motivation levels (Rivera and Currais, 2003; Ghatak, 2010). Bloom et al. (2003) find that healthier workers are more productive and earn higher wages. Dua and Garg (2019) find that capital deepening, human capital, technology, institutional quality and macroeconomic variables (i.e., government size and openness) are significant determinants of labour productivity of both developing and developed economies of the Asia-Pacific region.

Firm level global studies have also found significant role to technology, automation, capital deepening, foreign direct investment, and worker quality (or education). For instance, Papadougas and Volagiris (1999) show that labour productivity growth is positively related to the growth of net fixed assets per employee, export orientation, and R&D in Greece. However, firm size, employment growth, and firm age affect labour productivity growth negatively. Kroman, et. al. (2011) find that using industrial robots increases labour productivity in the EU. Similarly, Siegel and Griliches (1992) found a strong positive association between productivity growth and investment in computers. Brynjolfsson and Hitt (1993) also conclude that computers have made a substantial and significant contribution to output. The effects of ICT on labour productivity have been demonstrated in several other empirical works, such as Arvanitis and Loukis (2009), Badescua and Garces-Ayerbe (2009), Belorgey, Lecat, and Maury (2006), Ceccobelli, Gitto, and Mancuso, (2012), Engelbrecht and Xayavong (2006). Innovation, usually measured as R&D spending, and worker training or skill are generally considered labour productivity stimulating factors. Cohen (1995) Griliches (1995), among others, found a positive and significant effect of R&D on productivity. Qu and Cai (2011) estimated the effect of education and training on labour productivity in China using cross-sectional industry data. They found a positive relationship between workers' educational level and labour productivity in Chinese manufacturing industry. Foreign direct investment is related to productivity growth, as it is expected to come along with foreign technology, access to international markets, and exposure to competition. Tan and Batra (1995) have used industry-level data for several developing countries and found that education and training have a positive effect on productivity. Various studies have found a positive effect of FDI and foreign ownership on labour productivity (Harris, 2001; Harris and Robinson, 2003)..

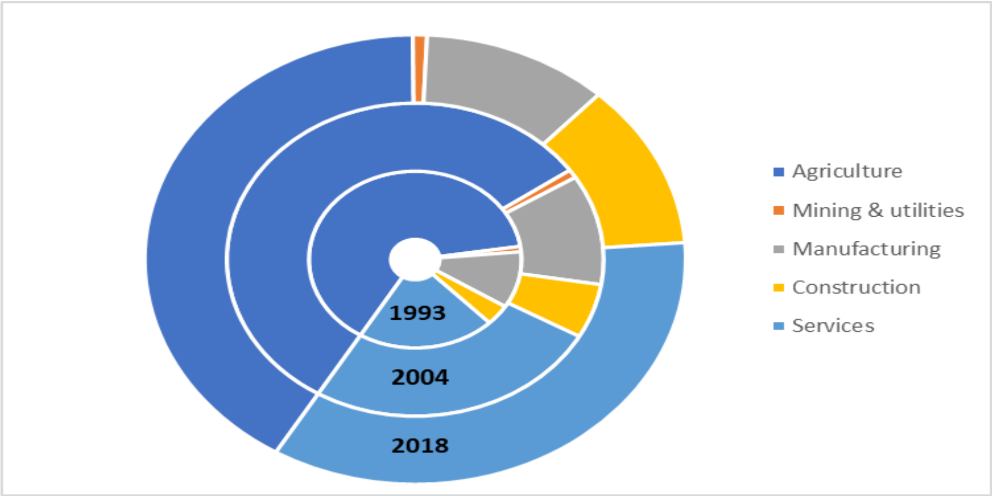
While most studies that examined the provincial level determinants of labour productivity are focused on Europe, the United States, and some on China, studies covering determinants of labour productivity using state level data for India is limited and this study adds to the literature by examining determinants of labour productivity by using both shift share approach and econometric approach.

3. Employment Structure in Indian States

In Figure 1, we depict the employment structure in the Indian economy using the India KLEMS data for the years 1993, 2004, and 2018. As is well known, agriculture still is the largest employment-generating sector in India. Although the sector has lost its prominence massively over the years, from 64 per cent in 1993 to 41 per cent in 2018, the sheer magnitude of the sector indicates the massive potential for growth-enhancing structural change. The paradox is, however, the stagnation in manufacturing jobs, which seems to defy the conventional structural transformation hypothesis. The manufacturing job share remained largely stagnant at around 11 per cent. While many emerging markets in Asia and Africa are argued to be facing premature deindustrialization (Rodrik, 2016), it is an important question whether India ever had the phase of industrialization. There has been no sign of any major uptick in India's manufacturing job share since the economic reforms in the early 1990s. While the services sector is the most common candidate to absorb all those workers that are moved away from agriculture, an interesting dynamic of India's structural transformation process is that of a substantial role of the construction sector (Erumban et al., 2019). The share of construction jobs increased by more than two-fold in 25 years, from below 4 per cent in 1993 to close to 12 per cent in 2018. The service sector, at the same time, also increased its job share, but not by this scale. However, given that the services sector is a combination of market and non-market services, which includes several industries, including the government sector, its relative size is much bigger, constituting 1/3rd of the total employment in 2018, compared to 1/5th of the economy in 1993.

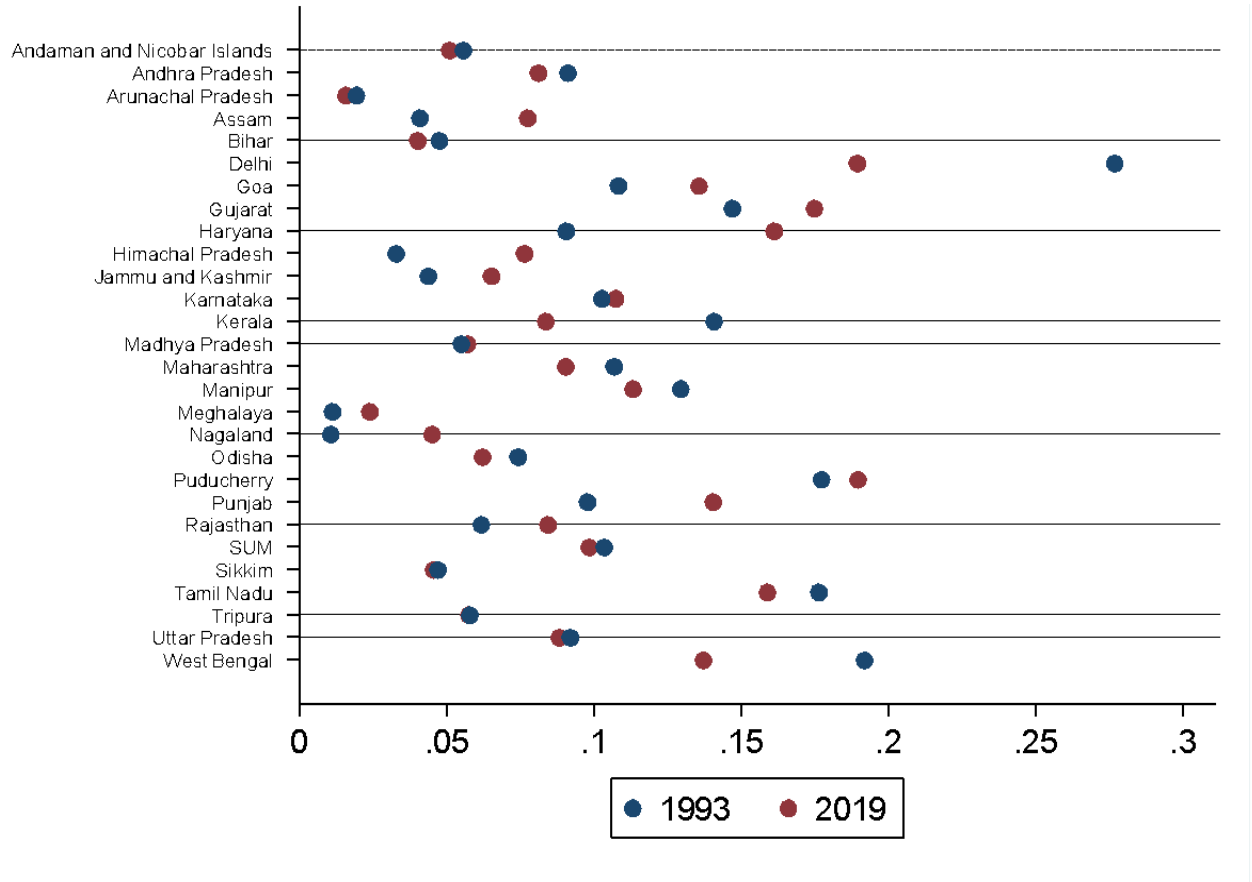
In Figure 2, we further examine the manufacturing share in total employment in each state to see whether the stagnation observed in the national economy is visible across the states. On average, the manufacturing job share remained about 10 per cent of all jobs over the last quarter of a century. Currently, the highest manufacturing share in total employment are in Delhi and Puducherry- both close to 1/5fh of the economy. Gujarat, Haryana, and Tamil Nadu are the next ones with a high manufacturing share - 15% or above. Punjab, West Bengal, Karnataka, Goa, and Manipur have 10 to 15 per cent of their jobs coming from the manufacturing sector. Except for Goa and Manipur, most of these are generally larger states, and in most of these states, manufacturing share further increased from the 1990s over the years. Exceptions are two large states, Tamil Nadu and West Bengal, and a small state Manipur, where we clearly see a deindustrialization trend.

Figure 1: Employment structure- All India national level



Source: India KLEMS
Note: the inner circle in the donut chart is for 1993-94, the middle circle is for 2004-05, and the outer circle is for 2008-2019.

Figure 2: Manufacturing Employment Share by state



Source: Authors' calculation using data from NSSO

On the other end, smaller North-Eastern states, viz., Arunachal Pradesh, Meghalaya, Nagaland, and Sikkim are the ones with the lowest manufacturing employment share (less than 5%), along with Bihar. Moreover, some of these states have also witnessed a retreat in manufacturing share over the years. Two other large states that have seen a fall in manufacturing job share are Maharashtra - the Indian state that is home to India's business capital Mumbai - and Kerala. With a nearly 6 per cent decline in the last 25 years, Kerala has had the largest decline after Delhi (by 9 per cent) across states in India. All in all, there appears to be an upward trend in manufacturing jobs in some states, which, however, was offset by a substantial fall in other states, leading to an overall stagnation of manufacturing share at the national level. The question of whether this reallocation of manufacturing job share across states has been productivity-enhancing – in other words, whether jobs were expanding in states which are relatively well off in terms of productivity or not gains added significance.

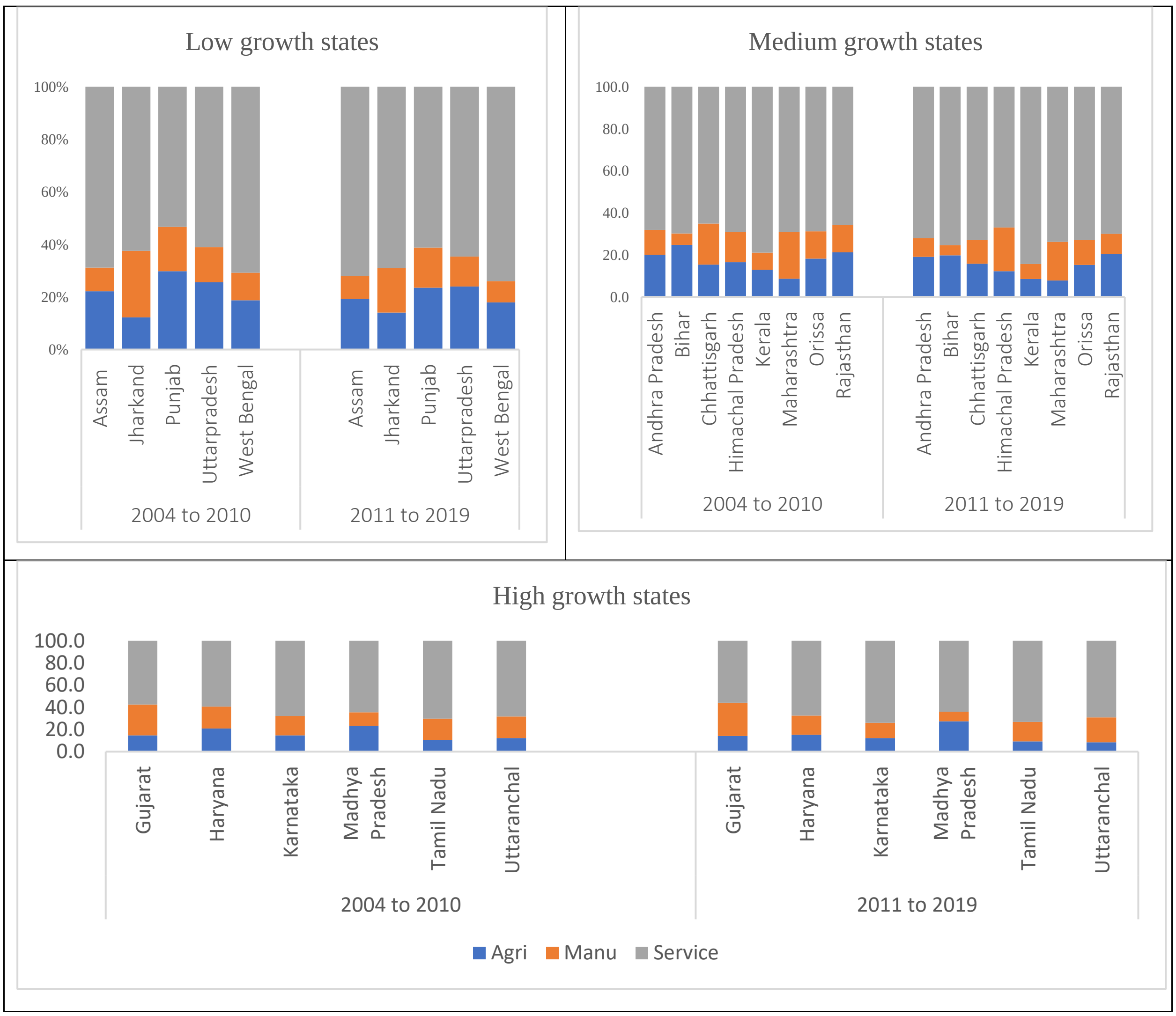
4. Labour productivity, productivity growth and structural change

This section evaluates the labour productivity and economic performance of 19 major states in India. Figure 3 shows the sectoral composition of value-added shares across states during two sub-periods, 2004 to 2010 and 2011 to 2019. Sectoral shares in the figure are presented by dividing the states into three groups based on average GDP growth rates for the period 2004 to 2019 - low median and high growth states. High-growth states include Gujrat, Haryana, Madhya Pradesh, Tamil Nadu, and Uttaranchal. Median growth states include Andhra Pradesh, Chhattisgarh, Kerala, Odisha, Bihar, Himachal Pradesh, and Maharashtra. And low growth states include Assam, Punjab, West Bengal, Jharkhand, and Uttar Pradesh. For most of the states, mirroring the national average, the agriculture share in state GVA have declined over the years. For low growth states (except for Punjab), the decline in agriculture share is moderate as compared to medium and high growth states[††]. The classical structural change theories, and past evidence on structural change in several advance economies suggests that as economy develops contribution of agriculture declines,

[††] Among high growth states Madhya Pradesh stands out to be an exception. For Madhya Pradesh, the annual average growth in agricultural GVA increased during 2004 to 2019 at 8 percent per annum surpassing the national average of 4 percent per annum. Gulati et al 2021, finds that the growth in agricultural GVA in Madhya Pradesh is due to major interventions of state government in terms of expanded irrigation, strong procurement system and improved road connectivity for farmers.

manufacturing plays a central role in the growth process and services sector takes the key role at a later stage. However, for India the classical pattern of structural change is not observed (Erumban et al., 2019). The decline in agriculture share across states is not associated with an increase in manufacturing share in GVA. While manufacturing growth remains stagnant, growth of service sectors has increased rapidly over the years. It is observed from figure 1 that services sector accounts for more than 65 per cent of GVA across all major states in India. During the subperiod 2011 to 2019, among the low growing states Jharkhand and Punjab accounted for largest increase in services sectors contribution to state GVA whereas for high growth states, the fastest rise in service sector was observed for Haryana, Karnataka, Chattisgarh and Bihar.

Figure 3: Sectoral Share in State GVA



Note: Services includes construction
Source: Handbook of Statistics on Indian States published by RBI

Table 1 below provides the growth rates in three indicators – employment, value added and capital stock – across 19 states for two sub-periods 2004 to 2010 and 2011 to 2019. It is observed that employment growth witnessed a revival in most of the states during the second subperiod as compared to the first one. Contrary to employment growth trend, capital stock showed a declining trend in the second subperiod for most of the states. Assam and Madhya Pradesh were an exception and witnessed a turnaround in growth of capital stock in the second sub period. Industrial states like Maharashtra, Gujarat and Tamil Nadu witnessed slower expansion of capital stock in second subperiod as compared to the first. GVA growth followed the pattern of capital stock growth. With slower expansion of investment during 2011 to 2019, GVA growth across states witnessed a declining pattern in second subperiod as compared to first subperiod.

Table1: Growth in employment, capital stock and Gross Value added by states

	Employment Growth		Capital Stock growth		GVA growth	
States	2004 to 2010	2011 to 2019	2004 to 2010	2011 to 2019	2004 to 2010	2011 to 2019
Gujarat	0.8	1.0	15.1	10.7	9.9	8.8
Haryana	-0.5	0.9	24.3	11.1	8.9	7.9
Madhya Pradesh	-0.7	2.8	11.6	23.9	7.6	7.7
Tamil Nadu	1.3	1.3	14.1	6.1	10.2	6.7
Uttaranchal	-0.3	1.1	25.8	6.4	13.5	7.1
Andhra Pradesh	0.5	0.2	16.2	11.4	7.3	7.0
Chhattisgarh	0.2	2.3	17.7	13.7	8.3	5.7
Kerala	-0.2	0.9	11.0	1.3	7.7	5.6
Orissa	-0.2	0.3	18.9	14.5	7.9	6.9
Bihar	1.5	1.3	12.8	11.6	8.6	6.7
Himachal Pradesh	0.5	2.3	18.9	6.4	8.1	6.6
Maharashtra	0.7	0.9	13.4	4.9	9.7	6.2
Assam	-0.7	1.6	9.7	11.9	5.3	6.1
Punjab	0.4	0.6	12.5	11.9	7.0	5.6
West Bengal	1.4	1.1	12.3	12.1	6.5	5.1
Jharkhand	-0.2	2.9	10.7	11.5	6.7	5.6
Uttar Pradesh	0.2	0.4	12.7	12.7	7.0	5.9

Source: Handbook of Statistics on Indian States published by RBI and ASI data
Note: Capital Stock estimates are based on

Moving to labour productivity, for period 2004 to 2019, the range of labour productivity growth across states varies from 8 to 14 per cent per annum. States with high GVA and capital stock growth - Haryana, Karnataka, Madhya Pradesh Gujarat – also recorded high labour productivity growth. On the other hand, states with low GVA growth, viz. Assam, Jharkhand, Uttar Pradesh, West Bengal recorded lower labour productivity growth during the same period.

Although the period 2004 to 2019 witnessed a rapid labour productivity growth, Figure 4 shows a tendency towards divergence of labour productivity across states. The lack of convergence (measured in terms of standard deviation) of labour productivity between high and low growth states is also established through the factor reallocation exercise done in the paper which shows that workers are not moving to more productive states and contribution of factor reallocation effects are rather marginal.

Figure 4: Growth rates of labour productivity in States 2004 to 2019

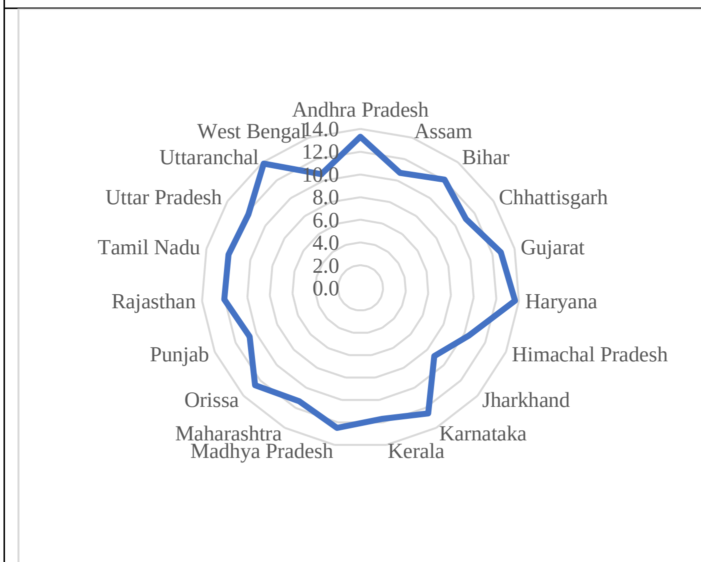
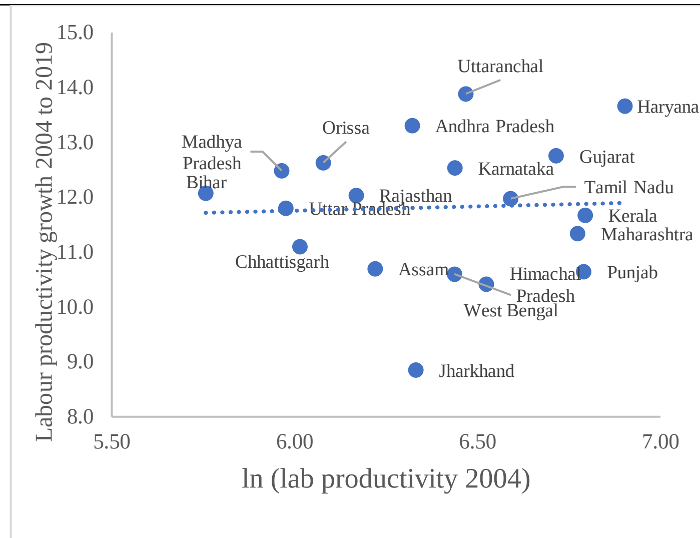


Figure 5: Labour productivity divergence across Indian States

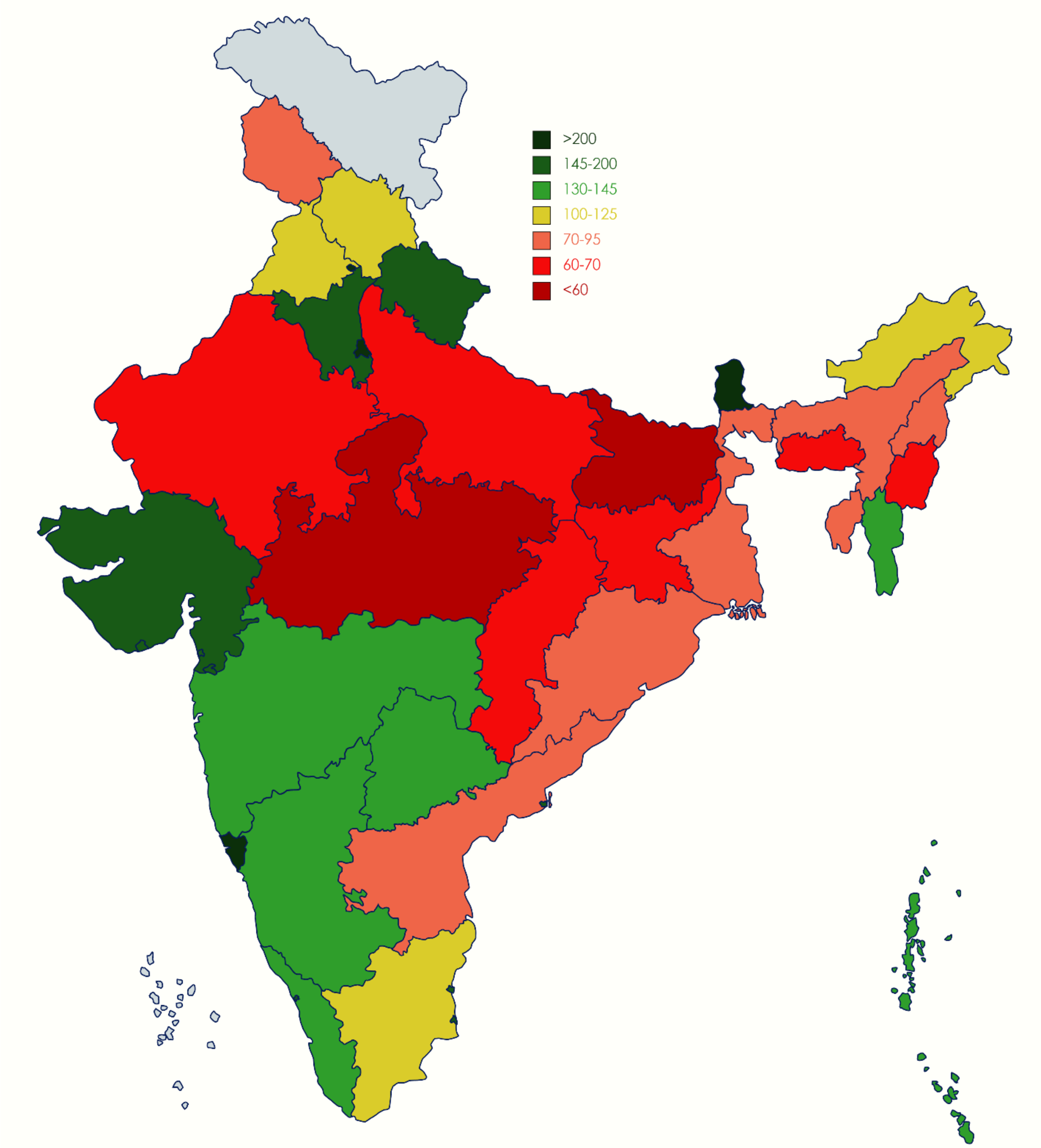


Source: Authors' calculations based on NAS and NSSO data

In Figure 6, we have a heatmap of Indian states by labour productivity levels in 2019. The map shows the productivity levels in each state in 2019 relative to the national average. Small states and union territories, Delhi, Goa, Chandigarh, and Sikkim, have the highest productivity level, varying from 2 to 3.5 times higher than the national average. Gujarat, Haryana, Puducherry, and Uttarakhand are the ones that follow, with productivity levels ranging from 145 to 200 per cent of the national average. Southern states, Kerala, Karnataka, and Telangana, along with Maharashtra and the northeastern state Mizoram, do pretty well, with their productivity levels in the range of 130-145 per cent of the national economy. Other states that are still above the national average but relatively lower than those mentioned above are Punjab, Tamil Nadu, Arunachal

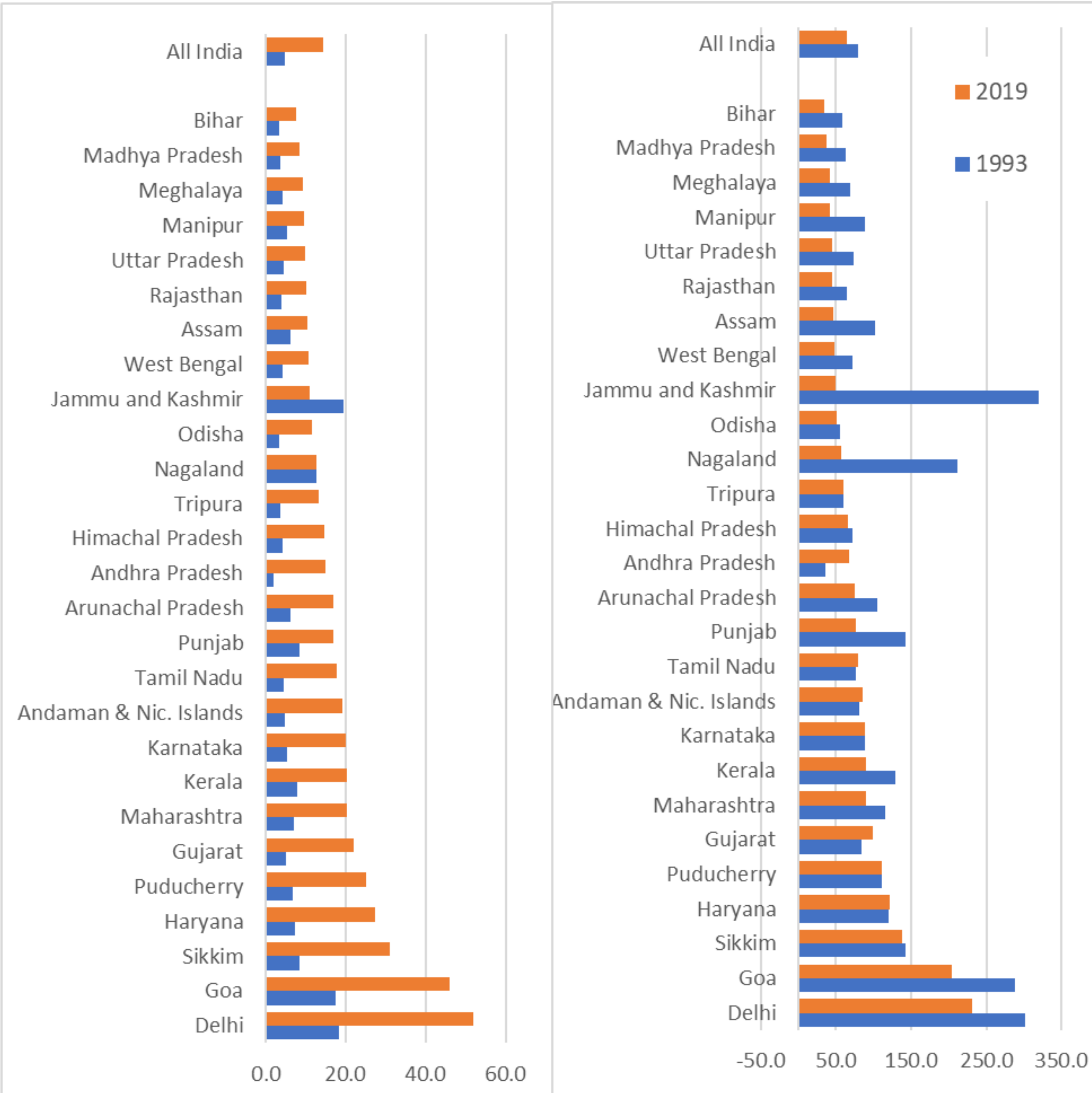
Pradesh, and Himachal Pradesh - their productivity levels range from just above the national average to a quarter higher.

Figure 6: Relative labour productivity levels in Indian states (All India =100), 2019



Note: Map generated using https://www.mapchart.net/
Source: author calculations using data from National Accounts Statistics, and NSSO.

Figure 7: Relative labour productivity levels in Indian states (left panel: US=100, right panel: China =100)



Note: The bars are the product of state labour productivity levels relative to national levels, and all India labour productivity levels relative to US (China). The relative levels of All India productivity are obtained at 2020 Purchasing Power Parity terms from the Conference Board Total Economy Database. A common PPP across Indian states is assumed. Numbers for China are based on the alternative estimates by The Conference Board (See , 2014).
Source: Authors' calculations using data from National Accounts Statistics, NSSO, and The Conference Board Total Economy Database.

All other states have their productivity levels below the national average, with Andhra

Pradesh, Odisha, West Bengal, Assam, Jammu & Kashmir, Tripura, and Nagaland ranging from 70 to 95 per cent of the national average, and Rajasthan, Uttar Pradesh, Jharkhand, Chattisgarh, Manipur, and Meghalaya in the range of 60 to 70 per cent. The remaining two states, Bihar and Madhya Pradesh are the worst-performing states in terms of their labour productivity levels, which stays below 60 per cent of the national average.

According to ‘The Conference Board Total Economy Database’, the average worker productivity in India, adjusted for purchasing power parities, was just 5 per cent of the United States level in 1993, which increased threefold to 15 by 2019. At the same time, productivity levels in China increased from about 6 per cent - quite close to India's levels - in 1993 to nearly a quarter of the US level by 2019. With a gallant assumption of equal purchasing power across Indian states, which is implicit in our comparison of productivity levels in this section, Figure 3 compares state-level productivities relative to the US and Chinese aggregate productivity levels. Even the best performing states in India, which are generally small states in terms of population and GDP, with limited influence on aggregate productivity, have their productivity in the range of 30 to 50 per cent of the United States. 10 of 27 states in the Figure have a productivity level below the relative levels of India's national economy in 1993, which has increased to 12 in 2019, suggesting the erosion of productivity in more states over time. This picture is more intense when we compare India's productivity levels with that of China. On average, India's labour productivity levels were about 80 per cent of the US levels in 1993, which declined to 65 per cent by 2019 due to faster productivity growth in China. This has caused most states to lose their relative productivity levels compared to China. A few notable exceptions are Andhra Pradesh, Tamil Nādu, Gujarat, and Haryana. Although the relative levels in smaller, well-performing states are still far above that of Chinese, they have substantially lost their productivity momentum over time.

5. Empirical Models and data

(i) Measuring Labour Productivity and worker reallocation

We measure labour productivity in this paper as real GDP divided by the number of workers. It should be noted that worker productivity is better measured if the number of hours is used as an indicator of employment. This is particularly true if there are many part-time, informal, or seasonal jobs in any industry. However, given the lack of data on the number of hours by industry and states in India, we use the second-best option, implicitly assuming that the growth in average working hours is proportional to the number of workers. We assume an aggregate production function for the Indian economy so that real GDP across sectors and states can be added to obtain the aggregate GDP at the national level.

$$Y_t = \sum_{i=1}^{n} Y_{i,t} = \sum_{s=1}^{S} Y_{s,t} = \sum Y_{i,s,t} \qquad (1)$$

where Y_t is the aggregate real value added at the national level, Y_i is the real value added in national sector i, Y_s is total real value added in state s, and $Y_{i,s}$ is the real value added in sector i in state s – all for year t.

Similarly, we can also obtain aggregate employment or the number of workers (L) as:

$$L_t = \sum_{i=1}^{n} L_{i,t} = \sum_{s=1}^{S} L_{s,t} = \sum L_{i,s,t} \qquad (2)$$

Now we define labour productivity (y_t) at different levels as:
Aggregate economy labour productivity at the national level: $y_t = \frac{Y_t}{L_t}$
Labour productivity for sector i in the national economy: $y_{i,t} = \frac{Y_{i,t}}{L_{i,t}}$
Aggregate economy labour productivity for state s: $y_{s,t} = \frac{Ys_{,t}}{L_{s,t}}$
Labour productivity for sector i in state state s[‡‡]: $y_{i,s,t} = \frac{Yi,s_{,t}}{L_{i,s,t}}$

With these formulations of labour productivity at various levels and following the shift-share decomposition method (Fabricant, 1942), we decompose labour productivity change at national, state, and sectoral level to contributions from productivity gains within sector-state boundaries and worker movement between sectors and/or states.

First, we decompose the change in aggregate national labour productivity between periods t and t_0 into within sector and between sector as:

[‡‡] Note that this is similar to saying labour productivity for state s in industry i, so that $y_{i,s,t}=y_{s,i,t}$

$$\Delta y_t = y_t - y_{t0} = \sum_i \Delta y_{i,t} \ . v_{i,t-1} + \sum_i \Delta v_{i,t} . y_{i,t-1} + \sum_i \Delta vu_{i,t} . \Delta y_{i,t} \qquad (3)$$

where Δ indicates the change in the variable in period t over t_0, and v_i is the share of employment in industry i in total national employment.

The first term in equation (3) is the product of a change in industry labour productivity in sector i and the employment share of that industry in the previous year, and hence is indicative of the contribution of any given industry to aggregate productivity growth, weighted by its relative employment size. We call this a within-industry productivity contribution or pure productivity contribution (Denison, 1967). The second term is the product of a change in the employment share of industry i and the productivity level of that industry in the initial period. Thus, it suggests whether jobs are expanding in sectors where productivity level was high - a static worker reallocation effect. This term will be positive if workers are moving to sectors where productivity levels are high. The last term is the product of a change in productivity and change in employment share, thus indicating whether job expansions are in sectors where productivity expansion takes place - a dynamic reallocation effect. If workers are moving to growing sectors or moving away from shrinking sectors (i.e., both these terms are either positive or negative), the reallocation term will be positive. If one of these terms is negative, i.e., either employment share is shrinking or productivity is declining, this term will be negative. The two reallocation term will help us understand whether worker reallocations are growth-enhancing or growth-reducing.

The second decomposition also uses the same aggregate labour productivity growth in the national economy but to delineate the effects of productivity growth within states and the worker movement across states. This decomposition provides us insight into the role of productivity growth within individual states, and the movement of workers from low productivity states to high productivity states, in driving aggregate national productivity growth.

$$\Delta y_t = y_t - y_{t0} = \sum_s \Delta y_{s,t} \ . v_{s,t-1} + \sum_s \Delta v_{s,t} . y_{i,t-1} + \sum_s \Delta vu_{s,t} . \Delta y_{s,t} \qquad (4)$$

Third, we decompose the productivity change in any given industry i (i.e. $\Delta y_{i,t}$ in the right hand side of equation 3) into the contributions from within state productivity gain in the given industry and worker reallocation across states in that industry. In this case, the reallocation term captures whether workers move across states, within the same industry, to locations where the industry is more productive.

$$\Delta y_{i,t} = y_{i,t} - y_{i,t0} = \sum_s \Delta y_{i,s,t} \cdot v^i_{s,t} + \sum_s \Delta v^i_{s,t} . y_{i,s,t-1} + \sum_s \Delta v^i_{s,t} . \Delta y_{i,s,t} \quad (5)$$

where v^i_s is the share of state s in total employment in industry i. Note that it is different from v_s in equation (4), which sht ehaare of state s I national employment, and v_i in equatin (3) which is the share of industry I in totalnational employment.

The fourth decomposition is the decomposition of aggregate labour productivity within any state (i.e. $\Delta y_{s,t}$ in equation 4) into to within industry productivity change in the state and across industry worker reallocation within the state. So, this captures how much a given industry contributes to a state's aggregate productivity growth and how much worker movements across industries within the state's boundary contribute.

$$\Delta y_{s,t} = y_{s,t} - y_{s,t0} = \sum_i \Delta y_{i,s,t} \cdot v^s_{i,t} + \sum_i \Delta v^s_{i,t} . y_{i,s,t-1} + \sum_i \Delta v^s_{i,t} . \Delta y_{i,s,t} \quad (6)$$

Finally, combining states and industries, we calculate the contribution of productivity growth within a state in any given industry to national productivity change. The reallocation in this decomposition captures workers' movement across states and sectors within the country.

$$\Delta y_t = y_t - y_{t0} = \sum_{i,s} \Delta y_{i,s,t} \cdot v_{i,s,t-1} + \sum_{i,s} \Delta v_{i.s,t} . y_{i,t-1} + \sum_{i,s} \Delta v_{i,s,t} . \Delta y_{s,t} \quad (7)$$

(ii) Determinants of Labour Productivity

As discussed in the previous section, labour productivity can change due to several factors, viz. use of capital equipment, technological changes, education, indicators of general health of state population, infrastructural development, financial development, institutional development, corporate governance, ease of doing business, competition, trade openness, free movement of labour and capital, etc. As a number of factors drive labour productivity, a multivariate production function, such as the popular Cobb-Douglas type function, can be estimated by linking labour productivity with capital stock and other factors. In the Indian context, estimation of a multivariate production function has to contend with various data limitations, especially with regard to longer time series data on province-wise employment and key structural parameters. Nevertheless, an attempt has been made to estimate a limited version of a multivariate production function of the following form:

$$\ln y_{s,t} = \beta_1 + \beta_2 \ln k_{s,t} + \beta_3 \ln mfg_{s,t} + \beta_4 \ln inf_{s,t} + \beta_5 \ln ger_{s,t} + \beta_6 \ln infra_{s,t} + \beta_7 \ln urban_{s,t} + \varepsilon_{s,t} \quad (8)$$

where k is capita stock per employee, mfg is the share of manufacturing sector in total employment, inf is infant mortality rate – a proxy for health, ger is gross enrolment ratio for higher education – a measure of education, $infra$ is infrastructure, and $urban$ is urbanization. All the variables are in natural log form. $\varepsilon_{s,t}$ is idiosyncratic shocks to labour productivity of state 's' at time 't'. A rise in use of capital per employee ($k_{s,t}$) is expected to increase labour productivity ($y_{s,t}$) directly while a rise shares of employment in manufacturing sector ($mfg_{s,t}$) may enhance the productivity indirectly by shifting from relatively less productivity sector (*e.g.* agriculture).

An improvement in health and skills of employees could raise the productivity. Good health is associated with reduced worker inability, lower days off work due to ill health, and higher motivation, leading to higher productivity over the life cycle (Rivera and Currais 2003). Furthermore, healthier workers are more productive and earn higher wages because they are physically and mentally more energetic and robust to job challenges (Bloom et al. 2003). Health indicator proxied by infant mortality rate ($inf_{s,t}$) reduction is expected to improve the health situation of workers in that state and thereby contributes to enhancing labour productivity.

Workers with skill and knowledge can undertake R&D and easily adapt to new technology (Nelson and Phelps 1996). Thus, education increases the effectiveness of labour input and hence productivity. Skills of employees are proxied by gross enrolments for higher secondary education ($ger_{s,t}$) which indicates that an increase in enrolment could produce skilled employees. Therefore, coefficient β_5 is expected to be positive.

Infrastructure is a key factor in facilitating the benefits of agglomeration economies. It is also an important input in the production process. Infrastructure enhances the productivity of other inputs, such as labour and capital. Further, it can attract input from elsewhere, and hence there is a direct link between infrastructure and productivity (Eberts and McMillen, 1999). Thus, infrastructural development ($infra_{s,t}$) facilitates higher productivity by raising efficiency of both labour and capital and hence, β_6 is expected to be positive. To empirically evaluate the impact of infrastructure on labour productivity an index of infrastructure is constructed by employing principal components analysis on four standardized infrastructure variables, *viz.*, per capita availability of power, per capita telephone connectivity, rail areas and road areas.

Greater urbanization ($urban_{s,t}$) could also help in augmenting labour productivity. Urbanization leads to the concentration of people and economic activity, promoting agglomeration economies. This, in turn, promotes positive spill over effects (Cicone and Hall 1996).

A key feature of timeseries data is the issue of autocorrelation, which is found to be prevalent when the model is estimated without dynamic specification. Therefore, the above equation is estimated by augmenting with lagged dependent variable. As a number of variables are used in above specification could be influenced by change in labour productivity, the estimation is performed by employing system generalised method of moments (GMM) approaches of Arellano-Bond-Bover (Arellano and Bover, 1995; and Blundell and Bond, 1998; Bond, 2002).

iii. Data

Most of the variables used in this study are obtained from the Reserve Bank of India (RBI)'s Handbook of Statistics on Indian states. We use the sixth edition of this series, which has updates on the existing data series, and its coverage has been expanded to incorporate three more indicators, viz., (i) agriculture and allied activities (ii) Social and Demographic indicators (State-wise Gross Enrolment Ratio) and (iii) Infrastructure (iv) Banking, and (v) Fiscal. The main variables in the study we draw from the handbook are GDP, bank credit, rail area, road area, telephone connection, power consumption, birth rate, death rate, infant mortality rate, social and capital expenditure, and shares of agriculture and manufacturing in GDP. In addition to the Handbook of Statistics on Indian states, we also rely on decennial census data by the government of India, National Sample Survey Office (NSSO) 's employment and unemployment surveys, National Statistical Organization (NS) 's periodic labour force surveys (PLS) the India KLEMS and Annual Survey of Industries (ASI).

To calculate labour productivity, we require data on output and employment by sector and state. The data on state-wise gross value added in real terms are obtained for each state and sector from the RBI Handbook of statistics on the Indian economy. The same source is also used to obtain data on all independent variables used in equation 8, except employment and capital stock. In what follows, we discuss the construction of employment and capital stock data by sector and state in detail. .

Employment (L): To construct state-sector employment series, we use the NSSO's Usual, Principal, and Subsidiary Status (UPSS) concept (Add a footnote on this concept, also Suresh, please check if this is correct, and add a foontote on the concept). From the Employment and Unemployment Surveys (EUS) of major rounds by NSSO and the PLFS of 2017-18 by (NSO) we collect information on workforce participation, which is the basic course for estimating employment. Prior to 2017, various rounds of NSSO unemployment and employment surveys were used to get employment numbers, and after 2017, we used the PLFS data.

Capital stock (K): Data on capital stock at the state levels are hard to obtain in India, and the information on investment and investment prices, which are essential to calculate such a series, is hard to compile. Therefore, we use an indirect approach to measure capital stock for individual states by combining data from the India KLEMS and ASI. The total capital stock in a given state s ($K_{s,t}$) is computed as the sum of capital stock in agriculture ($K_{s,t}^{AG}$), manufacturing ($K_{s,t}^{MF}$), and services ($K_{s,t}^{SR}$), i.e.

$$K_{s,t} = K_{s,t}^{AG} + K_{s,t}^{MF} + K_{s,t}^{SR} = \sum K_{s,t}^{i}$$

where the sector-specific capital stock data are obtained using the value added share of the sector in the aggregate national economy and the estimates of sectoral capital stock in the national economy in the India KLEMS database, i.e.

$$K_{s,t}^{i} = K_{N,t}^{i} * \frac{Y_{s,t}^{i}}{Y_{N,t}^{i}} \;; for\ i = AG \ \& \ SR$$

where $K_{s,t}^{i}$ is the capital stock in sector i in state s and year t, $K_{N,t}^{i}$ is the capital stock in sector i in the national economy in year t, obtained from the India KLEMS database, $Y_{s,t}^{i}$ is the value added in industry i in state s in year t, and $Y_{N,t}^{i}$. is the value added in industry i in the national economy in year t, obtained from the India KLEMS database. This approach is applied to agriculture and services sector, whereas for the manufacturing sector we use the shares of each state in total national fixed capital stock (FK) obtained from ASI.

$$K_{s,t}^{i} = K_{N,t}^{i} * \frac{FK_{s,t}^{i}}{FK_{N,t}^{i}} \; ; for \; i = MF$$

Labour productivity (*y*) in our study is measured as real value added divided by the number of employees (Y/L), and capital deepening (*k*) is measured as capital stock divided by the number of employees (K/L).

6. Empirical Findings

6.1 Productivity growth and structural change

As can be observed from Table 2, aggregate labour productivity at the national level grew faster in all sectors during 2004-2019 compared to the first decade (1993-2004) after the market reforms in India. In particular, the manufacturing sector has shown substantial improvement in labour productivity growth, followed by the services sector. At the aggregate level, most states also feature a similar trend - the 2004-2019 growth rate was higher than the previous period, except in Andhra Pradesh, Bihar, Goa, West Bengal, AN islands, Delhi, and Puducherry. A similar pattern is visible across states as well, with a few exceptions in each sector. Labour productivity growth in the manufacturing sector has been decelerating only in Goa, Andaman and Nicobar islands and Assam.

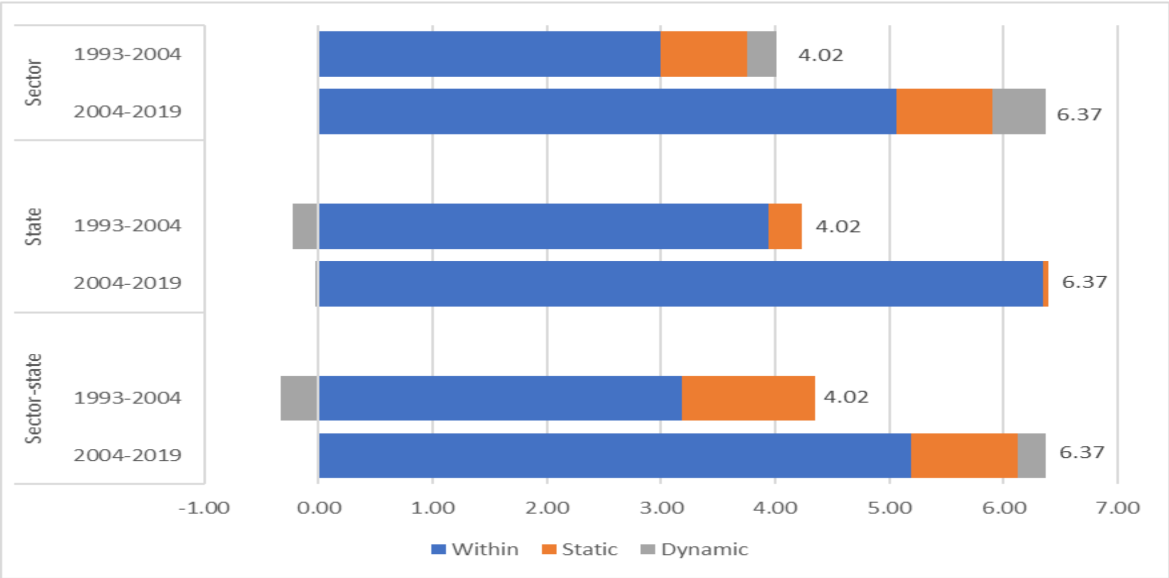
Table 2: Labour productivity growth in industries: Indian states

	Agriculture		Manufacturing		Services		Total economy	
	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019
Andhra Pradesh	6.8	5.6	10.0	8.5	10.8	6.9	10.7	7.5
Bihar	4.1	2.7	0.4	9.6	5.7	3.7	6.1	6.1
Goa	4.1	-0.6	11.9	-0.7	5.4	5.8	8.0	2.6
Gujarat	3.0	4.8	5.9	8.6	5.1	6.4	5.1	8.2
Haryana	0.4	6.1	2.6	5.4	7.3	8.0	4.3	7.8
Karnataka	-0.8	4.7	6.4	5.3	5.2	5.3	5.2	7.1
Kerala	2.3	0.1	2.5	9.8	2.5	5.5	3.6	5.7
Madhya Pradesh	-0.8	5.8	2.0	5.4	1.3	4.3	2.2	5.7
Maharashtra	1.0	3.3	2.9	7.6	3.5	6.2	3.3	6.7
Odisha	0.9	4.4	3.8	14.2	3.8	5.7	4.5	6.9
Punjab	0.5	4.9	0.2	5.5	2.5	4.0	1.6	5.3
Rajasthan	3.2	3.4	2.8	5.5	2.0	5.1	4.1	5.3
Tamil Nadu	1.9	3.9	4.6	8.8	6.5	5.2	6.2	6.5
Uttar Pradesh	-3.7	3.2	-0.2	7.9	0.6	6.4	-0.2	6.3
West Bengal	1.9	2.3	6.5	6.7	4.7	4.6	4.6	4.6
A&N Islands	5.6	1.4	4.9	-5.4	3.2	6.2	7.6	5.6
Arunachal Pradesh	0.7	3.8	12.1	1.7	2.6	1.8	4.2	5.4
Assam	-2.0	6.1	4.9	-0.2	0.9	1.7	1.1	4.7
Delhi	3.7	-4.5	1.0	4.9	4.6	5.6	4.8	5.4
Himachal Pradesh	4.5	1.2	5.6	7.4	2.7	5.2	6.0	5.8
Jammu and Kashmir	-2.0	-0.8	-13.0	5.3	-3.6	0.1	-4.1	1.1
Manipur	0.4	8.7	5.7	2.1	1.7	0.9	1.9	4.3
Meghalaya	4.2	4.3	-4.9	6.3	2.7	3.5	4.1	4.3
Nagaland	4.1	1.1	-18.5	1.4	-1.4	1.2	-0.8	2.3
Puducherry	0.6	4.1	12.4	2.8	5.4	4.1	8.8	4.5
Sikkim	-2.8	6.7	1.4	24.1	3.6	3.0	2.5	8.9
Tripura	4.0	3.1	3.0	1.7	5.8	7.8	6.1	6.2
SUM	**0.8**	**3.8**	**3.7**	**7.7**	**4.0**	**5.6**	**4.0**	**6.4**

Note: A&N Islands refers to Andaman and Nicobar Islands.

It can be observed from Figure 8 that the overall improvement in aggregate national labour productivity is primarily coming from within industry productivity growth. However, the role of sectoral worker reallocation is quite important. Around 1/5th of total labour productivity growth in the 2004-2019 period is from reallocation, of which more than 60 per cent is from static structural change. Moreover, the magnitude of structural change has increased over the periods. This indicates that workers are moving to sectors where productivity levels are higher and also to sectors where productivity growth is relatively better - thus suggesting a growth-enhancing structural change.

Figure 8: Aggregate labour productivity decomposition into sectoral and state reallocation effects



Note: Sector=contributions of within sector productivity growth (e.g., productivity growth in agriculture), and between sector worker reallocation (e.g., movement of workers from a low productivity sector to high productivity sector) to aggregate national labour productivity growth. State = contributions of within state productivity growth (e.g., productivity growth in Delhi), and between state worker reallocation (e.g., movement of workers from a low productivity state to high productivity state) to aggregation national level labour productivity growth. Sector-state= contributions of within state-industry (e.g., agriculture sector in Delhi) productivity growth, and worker reallocation across states and industries (from low productivity sector in Delhi to a high productivity sector in Delhi, or Gujarat) to national aggregate productivity growth.

Table 3: Decomposition of state labour productivity growth into industry contributions and reallocation across industries within the state

	State productivity growth		Within state's industries		Static (between industries within the state)		Dynamic (between industries within the state)	
	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019
Andhra Pradesh	10.7	7.5	8.5	6.3	0.7	0.7	1.5	0.5
Bihar	6.1	6.1	5.1	3.8	0.9	2.4	0.1	-0.1
Goa	8.0	2.6	8.9	1.4	-0.3	1.1	-0.7	0.1
Gujarat	5.1	8.2	4.5	6.9	0.4	0.5	0.2	0.8
Haryana	4.3	7.8	3.4	5.6	0.6	1.0	0.2	1.2
Karnataka	5.2	7.1	4.6	4.2	0.6	1.4	0.0	1.5
Kerala	3.6	5.7	2.2	4.8	1.3	0.7	0.1	0.2
Madhya Pradesh	2.2	5.7	1.5	4.9	0.9	0.7	-0.1	0.0
Maharashtra	3.3	6.7	2.5	6.0	0.7	0.3	0.1	0.4
Odisha	4.5	6.9	3.5	8.6	2.5	0.6	-1.5	-2.3
Punjab	1.6	5.3	1.2	4.2	0.4	0.8	0.0	0.3
Rajasthan	4.1	5.3	2.9	4.3	1.0	0.6	0.3	0.4
Tamil Nadu	6.2	6.5	4.7	5.0	0.7	1.3	0.7	0.3
Uttar Pradesh	-0.2	6.3	-1.4	5.6	1.3	0.6	-0.2	0.0
West Bengal	4.6	4.6	4.0	3.7	0.5	1.0	0.1	-0.1
Andaman and Nicobar Islands	7.6	5.6	5.3	4.5	1.4	0.6	0.9	0.5
Arunachal Pradesh	4.2	5.4	3.6	2.4	0.9	2.3	-0.3	0.7
Assam	1.1	4.7	1.2	2.3	1.1	3.1	-1.2	-0.7
Delhi	4.8	5.4	9.9	4.5	-0.3	0.6	-4.8	0.2
Himachal Pradesh	6.0	5.8	2.9	3.9	2.3	0.7	0.8	1.2
Jammu and Kashmir	-4.1	1.1	-4.8	0.0	2.7	1.9	-2.0	-0.8
Manipur	1.9	4.3	1.8	2.0	0.0	3.4	0.1	-1.1
Meghalaya	4.1	4.3	1.5	2.3	3.7	2.7	-1.1	-0.6
Nagaland	-0.8	2.3	0.3	0.8	-0.3	1.5	-0.8	0.1
Puducherry	8.8	4.5	7.5	4.4	1.3	0.5	0.0	-0.4
Sikkim	2.5	8.9	3.4	9.2	0.2	0.4	-1.1	-0.8
Tripura	6.1	6.2	10.4	5.5	0.4	5.6	-4.6	-4.9
SUM*	4.0	6.4	3.0	5.1	0.8	0.8	0.3	0.5

*Note: * SUM is the same as 'Sector' in Figure 5.*

Table 3 presents state wise decomposition of labour productivity growth to within industry effect and across state worker reallocation effects. For majority of states industry contribution accounted for more than 80 percent of aggregate labour productivity growth. When looked at the contribution of reallocation of workers across states that is, whether workers are moving to more productive states it is observed that the contribution of reallocation is limited. In terms of static reallocation, job shifting to industries with higher productivity have increased for Bihar, Gujarat, Karnataka, Kerela, Tamil Nadu and Tripura. For Gujarat, Haryana and Karnataka, where labour productivity has increased rapidly during 2004 to 2019 as compared to earlier sub-period, job shifting has increased and dynamic reallocation contributed for more than 10 percent of productivity growth. However, across all states, static reallocation term is much higher than dynamic reallocation - suggesting dynamic productivity losses due to spatial worker movements to states which are not growing faster.

In terms of sectors, labour productivity growth is higher in mining& utilities, manufacturing and services as compared to agriculture and construction. It is observed from Table 4 that static reallocation to high productive sectors is positive. That is to say, there is some degree of workers' movement from low productive to high productive sectors within states. However, the magnitude of static reallocation has been low in the second sub-period of 2004 to 2019 as compared to earlier sub-period. On the other hand, the dynamic reallocation is found to be negative across sectors, suggesting employment is not generated in sectors, which witnessed faster labour productivity growth.

Table 4: Decomposition of industry labour productivity growth into state contributions and reallocation across states within the industry

Productivity change by industry	Sectoral productivity growth (all India)		Productivity growth within states for the given industry		Static (Between states, within the industry)		Dynamic (between states, within the industry)	
	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019	1993-2004	2004-2019
Agriculture	0.8	3.8	0.8	4.1	0.3	-0.1	-0.3	-0.2
Mining & utilities	6.0	6.6	7.8	7.5	1.5	0.8	-3.3	-1.6
Manufacturing	3.7	7.7	3.8	7.5	0.4	0.3	-0.5	-0.1
Construction	1.0	0.0	1.8	0.9	0.6	-0.2	-1.4	-0.7
Services	4.0	5.6	4.0	5.6	0.2	0.1	-0.2	-0.1
SUM*	4.0	6.4	3.9	6.4	0.3	0.0	-0.2	0.0

*Note: * SUM is the same as 'State' in Figure 5.*

6.2 Determinants of Labour factor Productivity

Summary statistics of the panel variables presented in Table 5 indicate that variation in labour productivity and capital stock over time for each state exceeds variation across states, while variation between states for infant mortality rate, urbanization rate and manufacturing share is greater as compared to their change over time. Variation, both within and between, is non-zero, suggesting heterogeneity across states and over time, providing the rationale for the use of panel-based estimation approach.

Turning to regression estimates, we first present results based on the static specifications where the variables are contemporaneously related with labour productivity (Table 6). The estimated coefficient of capital stock per employee is found to be in the range of 0.36-0.40, lower as compared to capital income share of about 0.5 in case of aggregate data documented in KLEMS data 2021 release. This might indicate an underestimation of state-wise capital stocks in our approximation in the absence of official statistics on capital stock. As expected, a fall in infant mortality rate increases labour productivity. The coefficient β_5 is found to be positive but statistically insignificant across fixed effect and random effect model specifications. Infrastructure, urbanization and rise in manufacturing share are found to contribute positively to labour productivity as evidenced by their positive and statistically significant coefficients.

Table 5: Descriptive Statistics						
Variable		Mean	Std. dev.	Min	Max	Observations
ln (labour productivity)	overall	7.391186	0.685	5.757	8.952	N = 304
	between		0.366	6.736	8.048	S = 19
	within		0.585	6.075	8.333	T = 16
ln (capital deepening)	overall	3.972233	0.696	2.312	5.401	N = 304
	between		0.340	3.198	4.631	S = 19
	within		0.613	2.366	5.223	T = 16
ln (infant mortality)	overall	3.623845	0.451	1.878	4.369	N = 304
	between		0.393	2.424	4.077	S = 19
	within		0.238	2.997	4.180	T = 16
ln (gross enrolment ratio)	overall	3.620228	0.685	-0.062	4.498	N = 304
	between		0.480	2.682	4.327	S = 19
	within		0.501	0.427	4.982	T = 16
ln (infrastructure)	overall	4.60512	0.010	4.587	4.623	N = 304
	between		0.000	4.605	4.605	S = 19
	within		0.010	4.587	4.623	T = 16
ln (urbanization)	overall	-1.30323	0.465	-2.315	-0.430	N = 304
	between		0.472	-2.298	-0.722	S = 19
	within		0.068	-1.688	-0.994	T = 16
ln (manufacturin g share)	overall	-2.01458	0.447	-3.595	-1.088	N = 304
	between		0.427	-2.989	-1.241	S = 19
	within		0.164	-2.620	-1.487	T = 1

Note: N: Total number of observations; S: Number of states; T: Number of years.

Table 6: Static Regression Estimates: dependent variable = ln (labour productivity)

	Fixed Effect Model				Random Effect Model			
	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
$\ln k_{s,t}$	0.36***	13.16	0.40***	18.17	0.38***	14.48	0.37***	15.63
$\ln inf_{s,t}$	-0.49***	-7.07	-0.50***	-9.14	-0.48***	-8.71	-0.39***	-7.06
$\ln ger_{s,t}$	0.02	1.11	0.01	1.19	0.02	1.45	0.01	0.95
$\ln infra_{s,t}$	26.03***	11.96	16.21***	8.47	25.00***	12.79	24.38***	13.35
$\ln urban_{s,t}$			1.43***	12.51			0.56***	7.71
$\ln mfg_{s,t}$	0.07	1.56	0.13***	3.80	0.11***	2.85	0.08**	2.2
Constant	-112.06***	-11.07	-64.937	-7.26	-107.349	-11.87	-104.12***	-12.3
Number of obs.	304		304		304		304	
R-squared	0.97		0.98		0.92		0.89	

*Notes: ***,**,*: Significant at <1%, <5% and <10% levels, respectively.*

Table 7: Dynamic Panel Estimates: dependent variable = ln (labour productivity)

	Difference GMM				System GMM			
	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
$L.\ln y_{s,t}$	0.78***	31.49	0.83***	39.43	0.81***	47.71	0.84***	48.53
$\ln k_{s,t}$	0.09***	6.30	0.07***	5.22	0.07***	5.83	0.06***	4.98
$\ln inf_{s,t}$	0.01	0.38	0.03	0.93	-0.05***	-3.30	-0.05***	-3.26
$\ln ger_{s,t}$	-0.01	-1.19	-0.01	-1.57	-0.01	-1.42	-0.01	-1.40
$\ln infra_{s,t}$	4.93***	5.65	4.96***	5.52	2.97***	4.50	1.91***	2.83
$\ln urban_{s,t}$	0.25***	3.85			0.09***	6.60		
$\ln mfg_{s,t}$	0.07***	4.59	0.07***	4.07	0.04***	4.14	0.08***	6.72
Constant	-20.85***	-5.23	-21.65***	-5.30	-12.01***	-4.07	-7.38***	-2.43
Long-term coefficients								
$\ln k_{s,t}$	0.40		0.38		0.34		0.38	
$\ln inf_{s,t}$	0.05		0.16		-0.24		-0.34	
$\ln ger_{s,t}$	-0.03		-0.05		-0.04		-0.04	
$\ln infra_{s,t}$	22.10		28.35		15.33		12.03	
$\ln urban_{s,t}$	1.14				0.47			
$\ln mfg_{s,t}$	0.33		0.41		0.22		0.52	
AR1	0.05		0.02		0.02		0.02	
AR2	0.80		0.74		0.61		0.43	
Sargan	1.00		1.00		1.00		1.00	

Notes: Sargan and autocorrelation test results are from two-step estimations while the coefficient estimates are based on one-step estimation.

P-values are reported against various post-estimation tests.

AR1 and AR2 are tests for first-order and second-order serial correlation, respectively.

Sargan tests are for checking the overidentifying restrictions for the GMM estimators.

****,**,*: Significant at <1%, <5% and <10% levels, respectively.*

Turning to the dynamic specification, Table 3 presents the estimates based on both difference GMM and system GMM estimates. As this approach can quickly lead to a large number of instruments and an overfitting of the model, we also report results by restricting the number of instruments.[§§] The coefficient on lagged labour productivity is estimated in a range of 0.78-0.84 across specifications, indicating a relatively greater degree of persistence (also found in a regression of economy-wide aggregate labour productivity). The capital stock coefficient is statistically significant, but the size of the coefficient falls noticeably as expected in a dynamic model. Hence, the long-term coefficient computed from the model is meaningful and comparable to the corresponding coefficient in static specifications. The long-term capital share coefficient is found in the range 0.34-0.40, almost similar to that in the static specification. The infant mortality rate is also statistically significant in system GMM, implying the importance of health in determining labour productivity. On the contrary, although the coefficient of the enrolment ratio is positive, it is statistically insignificant in all specifications indicating a negligible contribution of skills to labour productivity in Indian states. On the other hand, infrastructure and urbanization both have significant positive impact on labour productivity. A rise in manufacturing share also helps in raising productivity.

6. Conclusion:

In this paper, we use both static and dynamic regression models to identify the significant factors driving labour productivity growth. Further, we quantify the state-industry worker reallocation effects on aggregate productivity growth in India using a shift share technique. The results of shift share analysis at an aggregate level show the overall improvement in national labour productivity is primarily coming from within industry productivity growth, whereas 1/5th of total labour productivity growth in the 2004-2019 period is achieved from labour reallocation effects. When looked at the contribution of state-specific productivity growth and reallocation of workers across states - whether workers are moving to more productive states - we find that there is no sign of job expansion in states where productivity is growing faster. Combining the two aspects of shift

[§§] Specifically, we report results using lags 1 to 4 of variables as instruments.

share analysis, we find that the overall impact of static reallocation is positive, but the dynamic gains are limited.

The econometric models with static as well as dynamic specifications on determinants of labour productivity find that better health, developed infrastructure, higher capital-labour ratio, rise in manufacturing share and greater urbanization contribute positively to labour productivity. However, the enrollment ratio is found to be statistically insignificant across the specifications implying negligible contribution of skills to labour productivity in India. While the role of education is prominent in driving labour productivity in advanced countries, there is a scope for raising labour productivity in India by enhancing skills and improving the education system.

Thus, the analysis in the paper shows that there exist sizable productivity gaps between different sectors and states in India. For achieving growth-enhancing structural change it is important to reduce regulatory complexity and burdens, which would improve the ability of new firms to enter and compete in high-productivity sectors and regions. As manufacturing and service jobs are becoming skill intensive, significant investment in health and education, including at the tertiary education level, would increase the ability of workers to be mobile across sectors and states to work with new and more productive technologies. Better education and more room for dynamic labour relocation could help spread the likely gains of technology improvements more evenly. Where learning outcomes are poor, government investment in widespread internet access could broaden access to quality online schooling and training. A better-educated labour force would be less likely to be replaced by automation (World Bank 2022).

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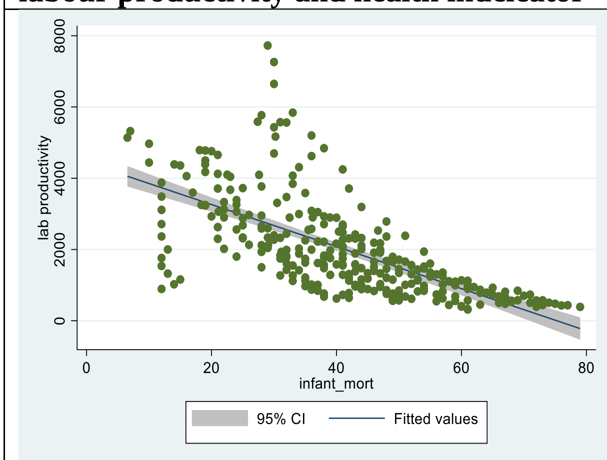
Appendix:

Literature has identified that good health and higher education level of workers positively influence labour productivity (Tara and Batra 2003, Ghatak 2010). In terms of health indicator, we have considered infant mortality rate as a proxy of population health status and for higher education we have considered gross enrollment ratio in higher secondary education as an indicator for skill level of population. It is observed from figure 4 below that there exists a negative relation between infant mortality and labour productivity across states. In most of the states, a decline in infant mortality rate increases labour productivity. For education, on an average as gross enrollment ratio in higher secondary education increases the labour productivity also increases (Appendix Fig 2).

Appendix Figure 1: Scatter plot between labour productivity and health indcicator



Appendix Figure 2: Scatter plot between labour productivity and indicator education

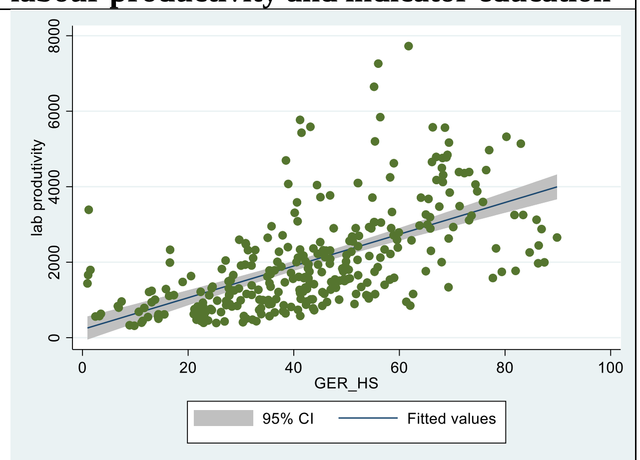


Table 2 below presents disaggregated statistics of health and education indicators for few selected years. It is observed in low GVA growth states, during 2006 to 2018, the decline in infant mortality rate has been the sharpest for Uttar Pradesh and Assam. Among median growth states, Himachal Pradesh, Odisha and Rajasthan showed the maximum decline in infant mortality rates and among high growth states fastest improvement was observed for Haryana and Madhya Pradesh. Interestingly Haryana and Madhya Pradesh also witnessed high labour productivity growth. For education, in low GVA growth states during 2006 to 2018 Punjab and Jharkhand have witnessed maximum rise in gross enrollment ratio in higher education. However, the growth in education is not reflected in high labour productivity growth across these two states. The high

GVA growing states, viz., Tamil Nadu and Uttranchal witnessed the fastest increase in gross enrollment ratio. These two states again do not have a high labour productivity growth.

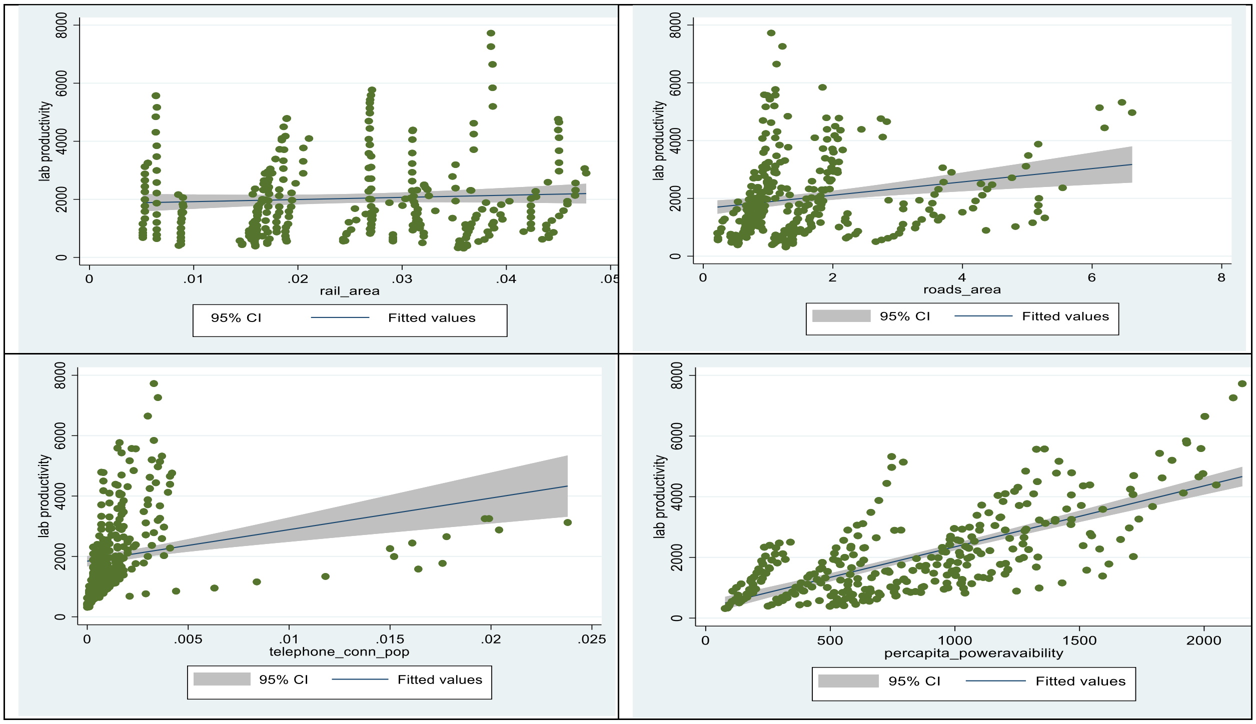
Appendix Table 1: State wise Indicators of health and Education-selected years

States/Indicators		Infant mortality rate			Gross enrollment ratio in higher secondary education		
Low GVA Growth states	Year	2006	2012	2018	2006	2012	2018
	Assam	67	55	41	14.38	24.63	30.93
	Jharkhand	49	38	30	3.48	27.65	38.89
	Punjab	44	28	20	31.06	59.56	68.17
	Uttar Pradesh	71	53	43	22	45.79	46.12
	West Bengal	38	32	22	24.25	40.95	51.73
Median GVA Growth States	Andhra Pradesh	56	41	28	40.8	79.39	46.88
	Bihar	60	43	32	11.19	13.73	26.39
	Chhattisgarh	61	47	41	23.04	42.2	52.08
	Himachal Pradesh	50	36	19	62.06	87.46	81.79
	Kerala	15	12	7	51.8	58.91	80.27
	Maharashtra	35	25	19	41.75	51.06	68.91
	Orissa	73	53	40	30.56	0.94	65.86
	Rajasthan	67	49	37	22.26	42.98	56.51
High GVA Growth States	Gujarat	53	38	28	27.75	37.89	41.2
	Haryana	57	42	30	35.62	54.89	56
	Karnataka	48	32	23	38.1	16.55	44.4
	Madhya Pradesh	74	56	48	31.02	29.61	43.72
	Tamil Nadu	37	21	15	48.59	65.97	72.31
	Uttaranchal	43	34	31	42.52	65.32	66.32

Source: Handbook of Statistics of Indian States

Apart from health and education, infrastructure have a significant positive impact on productivity (Veeramani and Goldar, 2005; Ghosh and De, 1998; Mitra *et al.*,2002; Sharma and Sehgal, 2010). It is observed from figure 6 that among infrastructure indicators like road, rail, telephone connectivity and power, per capita power availability is the most significant factor that drives labour productivity across states. Among low growth states, per capita power availability in all states except Punjab is well below the national average. Whereas among high growth states all states except Madhya Pradesh has per capita power availability higher than national average. For median growth states, per capita power availability is lower than national average for Bihar Chattisgarh and Odisha, whereas it is higher in Andhra Pradesh, Rajasthan and Himachal Pradesh.

Appendix Figure 3: Scatter plot between labour productivity and Infrastructure development



To sum up, we find that there exists a considerable divergence in labour productivity growth across states. Further, there is lack of job expansion in states with higher labour productivity growth and hence over time labour productivity growth is not converging across states. In terms of factors affecting labour productivity, there exist a negative relation between infant mortality and labour productivity across states. For education, on an average as gross enrollment ratio in higher secondary education increases the labour productivity increases. Apart from health and education, per capita power availability is an important factor that drives labour productivity growth across states. Given this background the next section attempts to examine the shift-share analysis of labour productivity. It also attempts to empirically analyse the factors that drive labour productivity for states.