Pathways to Jobs*

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Farzana Afridi [1]
Arjita Chandna[2]
Janani Rangan[3]
Jayanta Talukder[2]

Abstract

We focus on the manufacturing and services sectors, particularly the more labour intensive sub-sectors therein, as key drivers of job creation in India. We first highlight constraints on both the demand and supply sides of the labour market that hinder progress towards attaining the employment goals for *Viksit Bharat*. Next, we project the number of jobs that can be created through output growth in labour intensive manufacturing and services sub-sectors between 2025 and 2030, using different growth scenarios. The results suggest that inter-sectoral linkages can have a multiplicative effect on employment in the aggregate economy. On the supply side, we show that increasing the share of skilled work force by 12 percentage points through investment in formal skilling could lead to more than a 13% increase in employment in the labour intensive sectors by 2030. We conclude with policy prescriptions to boost aggregate demand and enhance workforce skilling.

Key words: jobs, economic growth, labour intensity, skilling
JEL classification: J21, J23, J24

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[1] Indian Statistical Institute (Delhi) and NCAER; Email: fafridi@isid.ac.in; fafridi@ncaer.org
[2] NCAER; Email: achandna@ncaer.org, jtalukder@ncaer.org
[3] School of Management, Mahindra University: janani.rangan@mahindrauniversity.edu.in
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1. Introduction

The story of India's economic trajectory has been a hopeful one over the last four decades - buoyed by the liberalisation of the 1990s, tempered by the global crises of 2008 and 2020, and continued resurgence post the pandemic. The world's most populated country enjoys favourable expectations of strong economic performance in the coming future, in terms of both the size of its economy -- a gross domestic product of US$ 7 trillion by 2030 (Economic Survey, 2023) -- and an economic growth rate that is the highest amongst all large, emerging economies (IMF, 2024), putting it on track to be the third largest economy in the world by 2027 (Ernst & Young, 2023).

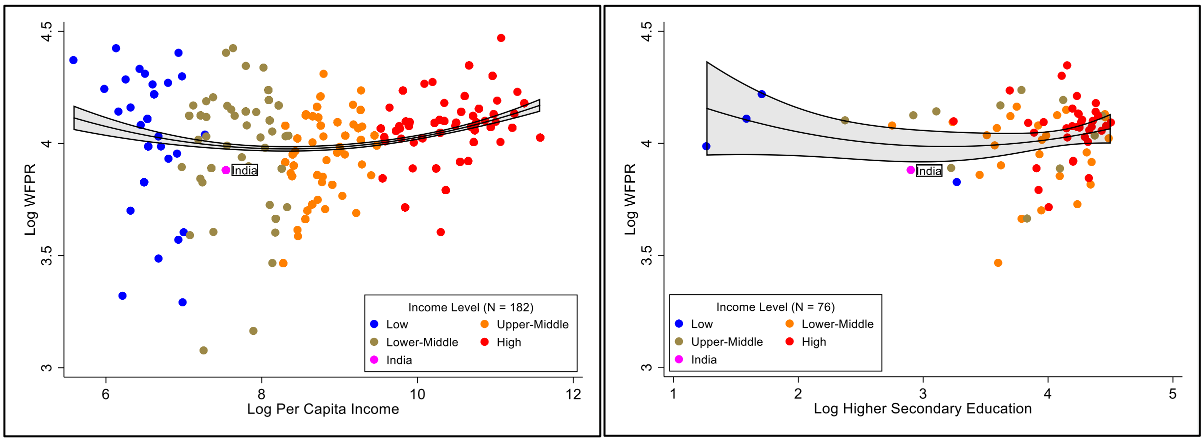
However, there has been growing concern regarding India's ability to productively engage its large and growing youth population. Since 2017-18, the country's working age population has increased by approximately 90 million, while we have added only about 60 million jobs – resulting in an annual shortfall of around 5 million jobs between 2018 and 2024 (PLFS reports). Furthermore, most of the recent increase in employment has been driven by either self-employment in rural areas or from informal services. These trends underscore India's slow transition from low- to high-productivity activity, and highlight the pressing need for not just jobs but also 'good' jobs. Hence both the quality and the quantity of work opportunities are under strain with a rising working age population.

The objective of this study is to highlight the role of an agile and dynamic policy framework, that focuses on creating a future- ready workforce to complement and advance the agenda of *Viksit Bharat*. As the India moves up the production value chain, it needs to simultaneously invest in both the quantity and the quality of its workforce. In order to address the challenge of job creation, therefore, we first highlight the constraints on both the demand and supply of labour.

1.2. Labour demand constraints

There are two characteristics of India's labour force that are striking – *first*, the low, overall labour force participation rate of about 50%, especially relative to comparable low-middle income countries. This also holds true when we look at work force participation rate (WFPR) by education rates (**Figure 1.1**).

Figure 1.1: Workforce participation rates (WFPR) by per capita income and education



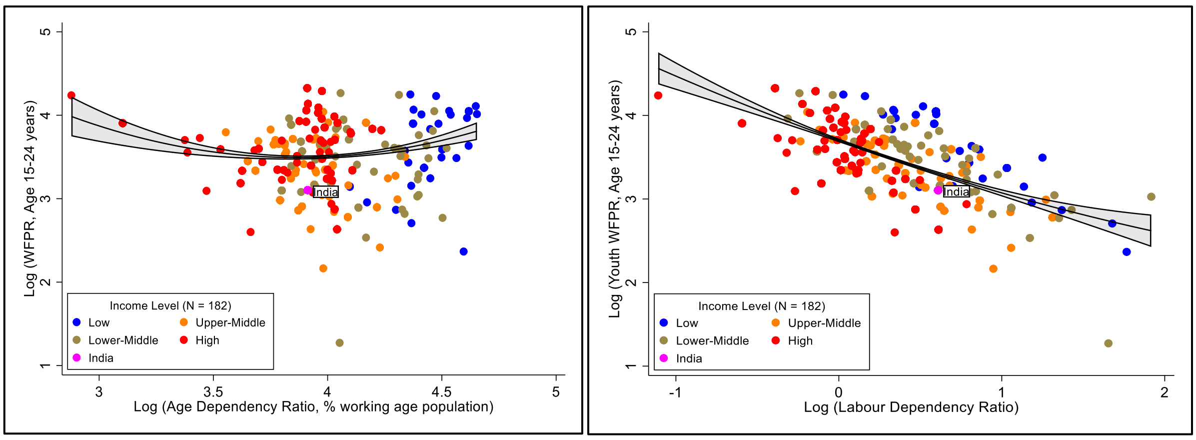
(a) WFPR vs per capita income (2018) **(b) WFPR vs Higher secondary education (2018)**

Source: Real GDP per capita (2015 USD) from World Bank database; Data for employment and population from ILOSTAT; Authors' calculations.

Note: i. WFPR (Workforce Participation Rate) = [(Total Employment/Total Population)*100] for age 15+; ii. Proportion of population with at least higher secondary education for ages 15+; iii. GDP per capital classifications follow the World Bank's 2017-18 thresholds; iv. 182 countries in Fig (a) and 76 countries in Fig (b); v. Both graphs use data from the year 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic; vi. 95% confidence interval bands.

In addition, India with its large youth population, has been unable to capitalize on the demographic dividend. Youth workforce participation in India is below the international trend line (**Figure 1.2**).

Figure 1.2: Youth workforce participation rate (WFPR) by dependency ratio



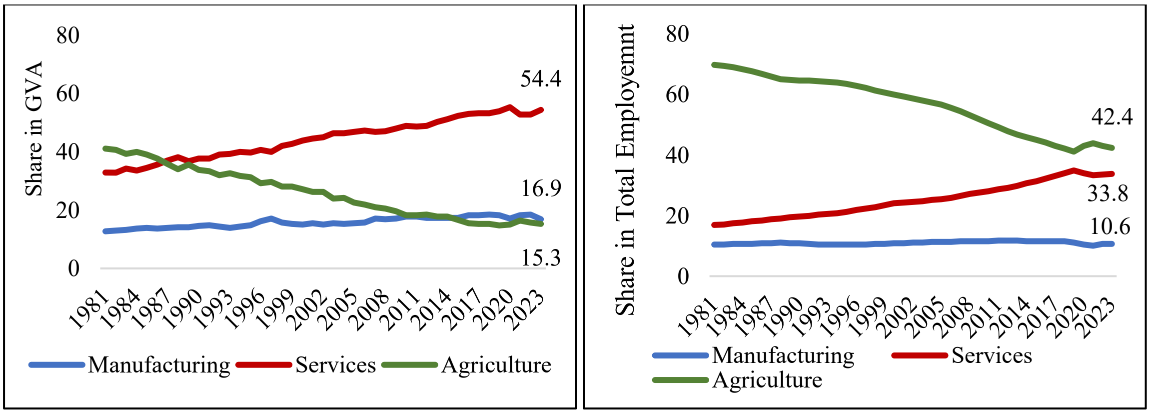
(a) Youth WFPR vs age dependency ratio (2018) **(b) Youth WFPR vs labour dependency ratio (2018)**

Source: Data on age from World Bank database; Data for employment and population from ILOSTAT; Authors' calculations.

Note: i. Youth WFPR = [(Employment/Population)*100] for ages 15-24; ii. The Age Dependency Ratio measures the dependence of non-working age groups (young and elderly) on the working-age population; iii. Labour dependency ratio measures the number of economically inactive individuals (people not in the labour force) per employed person; iv. Sample consists of 182 countries; v. Income classifications follow the World Bank's 2017-18 thresholds; vi. Both graphs use data from the year 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic; vii. 95% confidence interval bands.

The *second* accompanying characteristic of India's labour force, is the slow transformation, marked by an almost stagnant structure of labour force participation. Although, the proportion of workforce employed in agriculture has declined, it still remains the largest at around 45 %. This is despite a significant fall in agriculture's contribution to GDP (RBI KLEMS). Manufacturing sector's contribution to employment has been mostly stagnant with most of the labour shifting away from agriculture being absorbed by the services sector (**Figure 1.3**). These trends stand contrary to the historical experience of developed countries, where the structural transformation of the economy progressed from agriculture to manufacturing before moving into services.

Figure 1.3: Sectoral shares in total Gross Value Added (GVA) and employment (India)

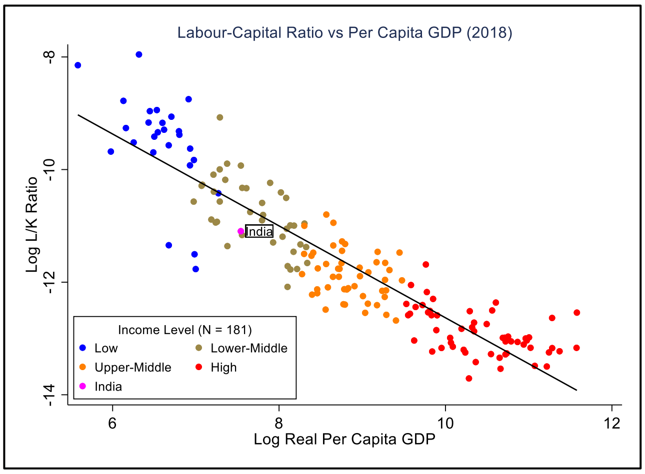


(a) Sectoral share in total Gross Value Added **(b) Sectoral share in total employment**

Source: India KLEMS, 2024; Authors' calculations.
Note: i. Gross Value Added (GVA) is in 2011-12 constant prices; ii. The data spans the period from 1981 to 2023, the latest year for which data is available.

These characteristics of India's labour force indicate constraints in productively absorbing its working-age population. We further highlight the demand-side constraints in labour absorption using the Penn World Table database, compiled by the Groningen Growth and Development Centre. We calculate the ratio of labour to capital utilized in an economy by dividing the number of persons employed (L, in millions of persons) by the capital stock at current PPPs (K, in million 2017 USD) of 181 countries in 2018 (latest pre-pandemic data available). The inverse relationship between the two variables is presented in the scatter plot in **Figure 1.4** for this sample of countries, where India falls in the set of low-middle income countries, but below the trend line. This indicates that for its given level of GDP per capita, the intensity of labour use in India's production technology is relatively low.

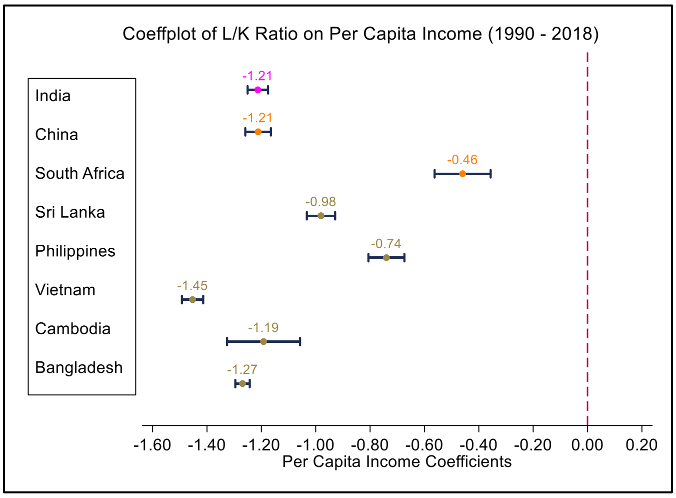
Figure 1.4: Labour intensity of production by per capita GDP (2018)



Source: Penn World Table (1990 -2018), Groningen Growth and Development Centre; World Bank database; Authors' calculations.
Note: i. L/K Ratio is the number of persons employed (in millions) divided by capital stock measured at constant 2017 USD prices (in millions); ii. The Per Capita GDP series is measured at constant 2015 USD prices; iii. Income classifications follow the World Bank's 2017-18 thresholds; iv. Sample consists of 181 countries; v. Both graphs use data from the year 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic.

Furthermore, we estimate the trend in the relationship between labour intensity and GDP per capita over three decades (1990 – 2018) for a sub-set of middle-income countries with economies that are comparable to ours. The coefficient plot below (**Figure 1.5**) shows the results of regressing the L/K ratio on per capita income to put into context India's rate of labour substitution as the GDP per capita grows.

Figure 1.5: Trends in labour intensity by per capita GDP (1990 – 2018) by country



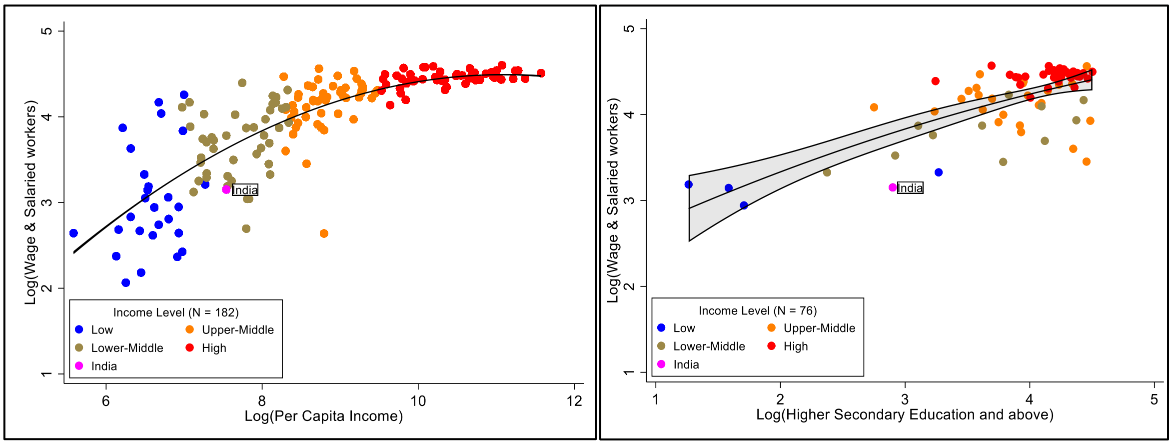
Source: Penn World Table (1990-2018), Groningen Growth and Development Centre; World Bank database; Authors' calculations.
Note: i. L/K Ratio is the number of persons employed (in millions) divided by capital stock at constant 2017 USD prices; ii. Per Capita Income is in constant 2015 USD; iii. Both variables are taken in log form. The coefficients can be interpreted as percentage changes; iv. The colour scheme distinguishes the World Bank Income Groups with the countries arranged in decreasing order of Per Capita GDP (2018) after India; v. 95% confidence interval bands.

While there is a very visible trend of declining labour intensity of production across these countries, as indicated by the negative coefficients, India stands out as one of the countries experiencing a particularly sharp decline. As per the RBI KLEMS data, between 1981 and 2023 there has been a monotonic decline in labour employed relative to capital - labour income share in value added has fallen by over 8%.

The low levels of labour force transition, coupled with stagnant structural transformation, suggests constraints in expanding the demand for labour. The declining labour intensity of production further exacerbates the challenge of job creation—particularly as production technologies increasingly favour capital over labour. With the advent of AI and automation the relative cost of labour is likely to increase further. Capital deepening is occurring even in labour intensive manufacturing and in services sub-sectors. This is both surprising and concerning for a country like India, which is not only labour abundant but is amidst a growing demographic dividend.

Not surprisingly, the data suggest that the paucity of "good" work opportunities impinges on the quality of work being done with significant underemployment across all occupations. Of those working, the share of self-employed in India is high, and rising (Afridi, 2025). This stands contrary to the historical trend globally, where rise in per capita GDP is associated with a fall in the share of self-employed and an increase in the share of salaried workers (**Figure 1.6**).

Figure 1.6: Proportion of wage & salaried workers by per capita GDP and education

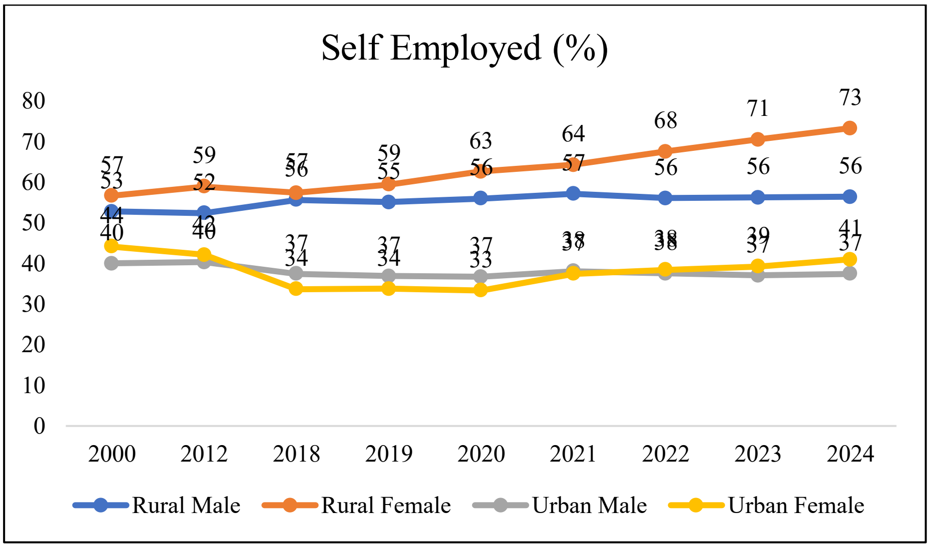


(a) Wage & salaried workers vs per capita income (2018) **(b) Wage & salaried workers vs higher secondary education (2018)**

Source: Data for GDP Per Capita (constant USD, 2015), and Wages and Salaried Workers is taken from the World Bank database; data on population by different levels of education is taken from ILOSTAT; Authors' calculations.
Note: i. Proportion of wage & salaried workers as percentage of total employment; ii. Proportion of population with higher secondary education and above for ages 15+; iii. Income classifications follow the World Bank's 2017-18 thresholds; iv. Figure (a) consists of 182 countries and (b) of 76 countries; v. Both graphs use data from the year 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic; vi. 95% confidence interval bands.

Strikingly, over 50% of the workforce is categorised as self-employed, the highest among all employment categories within the working-age population. This proportion has risen in recent years, particularly for rural women (**Figure 1.7**), along with a rise in the share employed in agriculture (post-pandemic). This suggests that self-employment is the fall-back option for the working-age population.

Figure 1.7: Trends in proportion of self-employed (India)



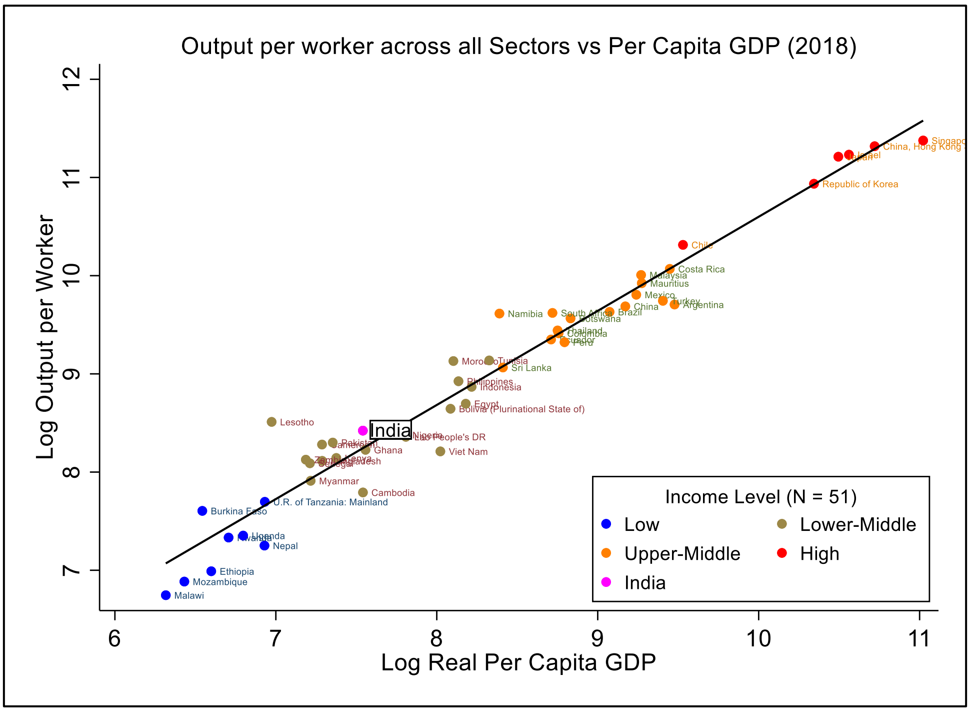
Source: Periodic Labour Force Survey (PLFS; 2017-18 to 2023-24); National Sample Survey 55th and 68th Round (NSS; 1999-00, 2011-12). Authors' calculations.
Note: i. Proportions are calculated as a percentage of total employment in each group; ii. The data spans the period from 1999-00 to 2023-24, the latest year for which data is available; iii. Sample size is of 16.9 crore in 1999-00 to 26.8 crore in 2023-24 iv. The NSS rounds are included to exhibit a longer trend.

1.2. Labour supply constraints

While the previous section highlights the capacity constraints faced by the Indian economy in absorbing the labour force, we cannot ignore the presence of constrictions on the supply side of the labour market. The low level of human capital among India's working age population potentially restricts access to gainful and quality work opportunities. We empirically examine the cross-country relationship between labour productivity and real per capita income and India's position relative to other countries. We, therefore, analyse the global patterns of labour productivity against per capita income with a specific focus on India's performance over the last three decades.

Using the Economic Transformation Database (ETD) from the Groningen Growth and Development Centre, we calculate labour productivity (or output per worker) as the gross value added (in constant US$, 2015) divided by number of persons employed for each sector. We pool data from 51 non-OECD countries over the period 1990 – 2018 for 12 sectors (Agriculture, Mining, Manufacturing, Utilities, Construction, Trade, Transport, Business, Finance, Real Estate, Government Services and Other Services) following the ISIC Rev 4 Industry codes in the Figure below.

Figure 1.8: Labour productivity and per capita GDP



Source: Economic Transformation Database (ETD; 1990-2018), Groningen Growth and Development Centre; World Bank; Authors' calculations.

Note: i. Output per worker is Gross Value Added (measured in constant 2015 USD) divided by persons employed; ii. GDP Per Capita is measured in constant 2015 USD prices; iii. Income classifications follow the World Bank's 2017-18 thresholds; iv. Sample consists of 51 non-OECD countries, as available in the ETD.

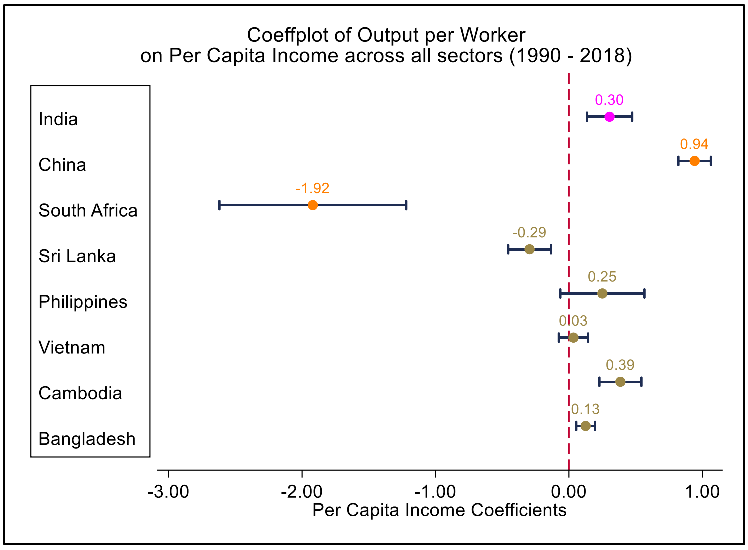
The scatter plot (**Figure 1.8**) indicates, expectedly, that output per worker rises with increase in GDP per capita. India is slightly above the trend line. However, the analysis also shows that in order to reach the level of per capita GDP of high-income countries, India will need to increase its labour productivity significantly.

To assess the growth in labour productivity over time in India, we examine its relationship with real per capita income growth. Specifically, we regress the log of labour productivity of country *i* in year *t* on the log of real per capita income, as follows.

$$Log(Labour\ Productivity)_{it} = \beta_0 + \beta_1 Log(Per\ Capita\ GDP)_{it} + \varepsilon_{it} \qquad (1.1)$$

We use the same sample of low- and middle-income countries as previously, and test for significant differences in estimated coefficients between India and the other countries.

Figure 1.9: Output per worker and GDP per capita (1990-2018)

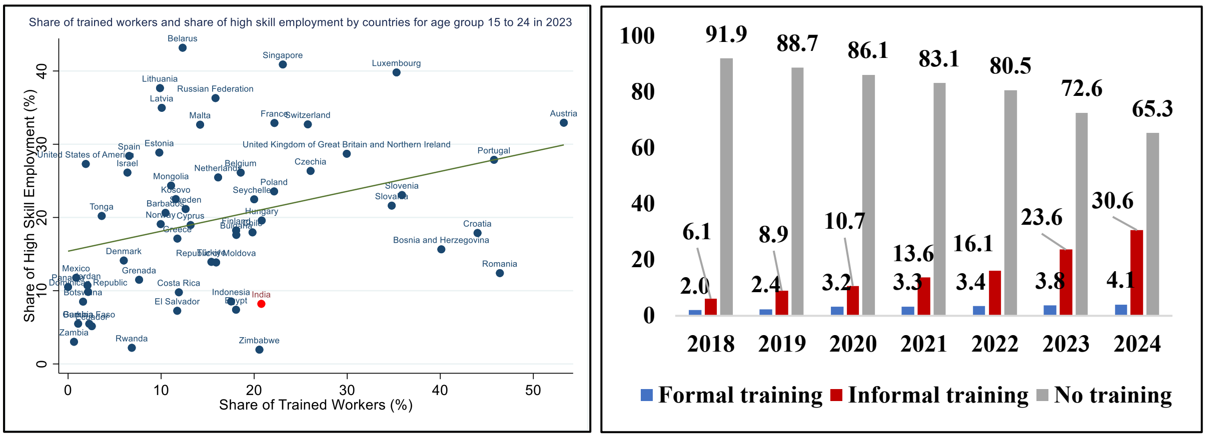


Source: Economic Transformation Database (1990-2018), Groningen Growth and Development Centre; World Bank; Authors' calculations.

Note: i. Output per worker is Value Added (constant 2015 USD) divided by persons employed; ii. Per Capita GDP is in constant 2015 USD; iii. Both variables are taken in log form. The coefficients can be interpreted as percentage changes; iv. The colour scheme distinguishes the World Bank Income Groups with the countries arranged in decreasing order of Per Capita GDP (2018) after India; v. 95% confidence interval bands.

The coefficient plot in **Figure 1.9** shows that while India's labour productivity has been growing along with growth in per capita income and keeping pace with similar lower middle-income economies, labor productivity growth is slower than that of China. The relatively slow growth in labour productivity, is accompanied by low share of high skilled youth employment for the given proportion of skill trained youth workers in India (**Figure 1.10a**). The cross-country analysis suggests that India's quality of skill training may not be adequate to translate into high skill employment.

Figure 1.10: High skill employment and trends in worker training



(a) Share of trained workers vs high skill employment **(b) Distribution of workers by training in India**

Source: ILOSTAT, International Labour Organization (2023); PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. ILOSTAT provides data on the working-age population (ages 15+) with vocational education or training, disaggregated by age group as well as data on the total working-age population, disaggregated by age group. This allows for the computation of the share of youth (ages 15-24) with vocational training across countries; ii. ILOSTAT also reports data on employment by occupation skill level based on the International Standard Classification of Occupations (ISCO) which is used to compute the share of employment in high, medium and low skill occupations; iii. Figure (a) based on sample of 58 countries.

More worryingly, for India's labour force as a whole, although the proportion of unskilled has been falling, the proportion with formal training has been more or less stagnant (**Figure 1.10b**). It is not surprising, therefore, that the supply-side constraint on the quality of labour lowers the probability of being employed (as we discuss later in Section 3).

The analysis indicates that India needs to sharply increase the productivity of its labour force and invest in increasing the skill levels of it working age population to become "*viksit*". The low and poor-quality engagement of the working-age population, combined with increasing capital deepening across sectors, points to pressing challenges on both the supply and demand sides of the labour market. These dual constraints—limited supply of skilled labour and the economy's insufficient capacity to productively absorb the workforce—need to be urgently addressed. This study, therefore, aims to examine both dimensions to inform the creation of sustainable and inclusive employment opportunities in India.

In the following sections, we focus our analysis on the manufacturing and services sectors — particularly the more labour intensive sub-sectors — as the share of agriculture in gross output has been steadily declining. Although we have seen an uptick in employment in agriculture due to the pandemic, the future of job creation lies in the manufacturing and services sectors. The data thus far, suggest that the services sector may have highest potential to generate jobs in the future – given its increasing share in GDP and contribution to total employment. We, therefore, analyze the impact of sectoral output growth and skilling on job creation in services and manufacturing sectors, over the next five years, until 2030.

In the **next section**, we propose measures to ease the demand side constraints and project the number of jobs that can be created through growth in manufacturing and services sectors, particularly the labour intensive sub-sectors until 2030. In **Section 3**, we assess the potential impact of skill and vocational training on improving job opportunities in manufacturing and services sectors between 2025 and 2030. **Section 4** concludes with policy implications.

2. Loosening the labour demand constraints

Having examined and set into context the constraints on both the supply and demand sides of the labour market, as well as India's relative position in terms of labour productivity and demographic potential, we now turn to the structural aspects of job creation. Specifically, we explore how sectoral patterns of production and investment influence labour demand. The following section focuses on identifying the sectors and sub-sectors within manufacturing and services that have the greatest potential for employment generation by analysing trends in labour intensity and employment elasticity over the past four decades. This forms the basis for projecting job creation until 2030 and informing targeted policy interventions.

2.1. Trends in the labour intensity of production across sectors (1981 – 2023)

To assess the potential for future job creation, we begin by analysing trends in labour intensity across the agricultural, manufacturing, and services sectors over the period 1980 - 81 to 2022-23 (1981 and 2023, henceforth). Using data from the RBI KLEMS database, we examine how labour has been utilised relative to output in each sector. This helps us understand the extent to which different sectors have contributed to employment generation and whether their production structures have become more or less labour intensive over time.

2.1.1. Ratio of physical labour to physical capital across sectors

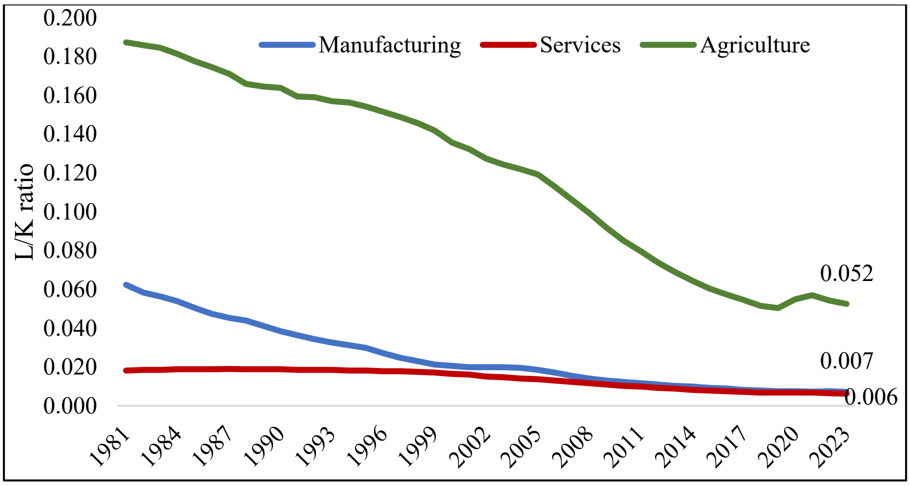
We define labour intensity as the ratio of number of persons employed (L, in '000s) and capital stock at constant prices (K, 2011-12, Rs. crore). The K/L ratio has been widely used in the literature to understand trends in capital intensity across sectors (Hasan et al., 2013; Kapoor, 2014).
The L/K ratio measures the relative dependence on labour compared to capital. High L/K ratio implies that more labour is used per unit of capital. This is indicative of labour intensive production. Since our objective is to identify sectors that absorb more units of labour, the L/K ratio is a more appropriate measure.[1] Measures such as labour income as a share of value added may be influenced by changes in real wages and cost of capital.

We highlight a clear decline in the L/K ratio across sectors, over the years, indicative of capital deepening as shown in **Figure 2.1**. It is interesting to note that the L/K ratio of the services sector is lower than that of the manufacturing sector. While the number of employed persons is higher in services than in the manufacturing sector, the value of capital stock in the services

[1] In the Indian context, the ASI data has been used predominantly to compute capital intensity (Kumar, 2021). The advantage of this study, however, is that the India KLEMS database allows us to incorporate both formal and informal manufacturing enterprises.

sector is higher than that of the manufacturing sector – likely contributing to the lower L/K ratio. The decline in L/K ratio in the services sector seems to have occurred at a faster pace post 2002. However, this decline has been sharpest in agricultural sector, followed by manufacturing.[2]

Figure 2.1: Labour to capital (L/K) ratio by sector



Source: India KLEMS, 2024; Authors' calculations.
Note: i. L refers to Number of persons employed (in '000s) and K is the Capital stock in constant 2011-12 prices (Rs. Crores); ii. The labour to capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data.

In order to identify industries which are relatively more labour intensive and hence likely to generate greater job opportunities, we classify sub-sectors within manufacturing and services as labour or capital intensive using the L/K ratio since it reflects the use of physical input quantities rather than input costs. Sub-sectors with median[3] or above labour intensity as relatively labour intensive and those with below median L/K ratios as relatively capital intensive. [4]

Based on this classification, the sub-sectors identified as relatively more labour intensive include manufacturing sub sector's such as, *Textile and textile products, Food products and beverages, Paper products and printing*, as well as service sub-sector such as *Trade, Hotels and Restaurants, Education,* and *Transport and Storage*. These industries consistently exhibit median or above-median labour-to-capital (L/K) ratios across the reference period. In the analysis that follows, we focus both on the aggregate manufacturing and services sectors and

[2] We observe the same decline in labour intensity in formal manufacturing as in the entire manufacturing sector, discussed above, and a convergence of the L/K ratio in the total manufacturing sector to that of formal manufacturing (ASI data) between 1981 and 2023.
[3] The median labour to capital ratio for the manufacturing sector is 0.006 and 0.009 for the services sector, respectively. The sub-sectors with values equal to and above median of the manufacturing or services sector are classified as labour intensive.
[4] Interestingly, using this classification, we find that the observed decline in labour intensity has been sharp in the more labour intensive sub-sectors in both manufacturing and services, while the ratios have been relatively stable in the capital-intensive sub-sector sectors.

on some of these selected labour intensive sub-sectors to estimate their contribution to employment generation and assess their potential to absorb additional labour.

2.2. Employment elasticity across sectors

A sector may be classified as labour intensive based on its high use of labour relative to capital, but this alone does not guarantee strong job creation. If output in such a sector remains stagnant or grows slowly, its contribution to employment generation may be limited. To gain a clearer picture of the actual employment potential of these identified labour intensive sectors, it is essential to consider not just their input structure but also their responsiveness to output growth.

We therefore estimate sectoral employment elasticity, which measures the percentage change in employment resulting from a one percentage point change in economic output. This metric helps assess an economy's ability to generate jobs as it grows, and whether output expansion translates into proportional increases in employment. In essence, employment elasticity summarizes the sensitivity of job creation to economic growth, offering insight into which sectors are most effective in absorbing labour when production scales up.

We calculate employment elasticity across sectors using two standard approaches widely applied in the literature:

a. Compound annual growth rate (CAGR) approach (Rangarajan *et al.*, 2007; Papola *et al.*, 2012)

b. Log-log regression (Misra and Suresh, 2014)

Our analysis begins with estimating overall employment elasticity by broad sector to understand the general trends. We then focus specifically on the sub-sectors within manufacturing and services that were previously identified as labour intensive based on the labour-to-capital (L/K) ratio. For this purpose, we use data from the India KLEMS database, which offers consistent and comparable time-series information on sectoral output and employment.

a. ***Compound Annual Growth Rate (CAGR) Approach***

The CAGR method is used to estimate **arc elasticity**, which represents the average responsiveness of employment to output growth over a specified period. Employment elasticity in this framework is calculated as the ratio of the compound annual growth rate of employment to the compound annual growth rate of real value added:

$$\text{Employment elasticity} = \frac{CAGR\ of\ employment}{CAGR\ of\ value\ added} \qquad (2.1)$$

For instance, for the period 2012 to 2023,

$$\text{CAGR of employment} = \left(\frac{L^{2023}}{L^{2012}}\right)^{\frac{1}{11}} - 1$$

$$\text{CAGR of value added} = \left(\frac{Y^{2023}}{Y^{2012}}\right)^{\frac{1}{11}} - 1$$

Where, L is the number of persons employed (in '000s) and Y is the sector-wise value added in constant 2011-12 prices (in Rs. Crore).

b. ***Log-Log Regression***

To complement the CAGR-based estimate, we also compute **point elasticity** by estimating a log-log regression model. The log of employment in a sector is regressed on the log of value added of the sector.

$$LogL_t = \alpha + \beta LogY_t + e_t \qquad (2.2)$$

Where, L is the number of persons employed (in '000s) and Y is the sector-wise value added in constant 2011-12 prices (in Rs. Crore).

2.2.1. Overall employment elasticity

Table 2.1 shows that employment elasticity is higher in the services sector as opposed to manufacturing. While the manufacturing sector's employment elasticity shows a significant decline between the 1980s and 2010s (*p*-value = 0.004), the elasticity values for services are not significantly different in 2010s from the levels in the 1980s.[5]

[5] The difference between the 1980s and 2010s (1981 to1990 and 2011-12 to 2022-23) is significant (*p*-value = 0.004), indicative of a significant change in the elasticity of the manufacturing sector over this period. For services, while the difference between the 1980s and the 2010s is not significant (*p*-value = 0.874), the elasticity values between the 1990s and 2000s are significantly different (*p*-value = 0.000).

Table 2.1: Employment elasticity estimations based on CAGR and log-log methodology

Sector		Year			
		1981 to 1990	1991 to 2001	2002 to 2011	2012 to 2023
Manufacturing	CAGR	0.329	0.335	0.215	0.220
	Log-log	0.357***	0.268***	0.188***	0.134*
		(0.023)	(0.029)	(0.028)	(0.064)
Services	CAGR	0.512	0.528	0.382	0.532
	Log-log	0.514***	0.513***	0.378***	0.523***
		(0.010)	(0.014)	(0.015)	(0.055)

Source: RBI KLEMS, 2024; Authors' estimations
Note: We estimate employment elasticity (CAGR in top row and log-log in bottom row) for sectors from 1980–81 to 2022–23. The sample period is divided into four broad time periods to illustrate the evolution of elasticity over time. Labour is defined as the number of persons employed (in '000s). Value added is in constant prices (2011-12) prices (Rs. crore). The standard errors are mentioned in parenthesis. The significance levels are denoted by ***, **, * for 1%, 5% and 10% levels, respectively. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic.

Next, we estimate employment elasticity for the sub-sectors within manufacturing and services that were previously identified as relatively more labour intensive (**Table 2.2**). We observe a consistent fall in employment elasticity across the labour intensive manufacturing sub-sectors. However, employment elasticity has increased significantly in the education, health and financial services sectors between 1981 and 2023. This indicates that the potential of the labour intensive services sub-sectors to create job opportunities is significant.[6]

[6] Interestingly, employment elasticity in formal manufacturing has been increasing overall, as well as in the labour intensive sub-sectors, unlike for the entire manufacturing sector for this period (ASI data). This indicates, that the observed decline in employment elasticity is driven by the informal manufacturing sector.

Table 2.2: Employment elasticity estimations based on log-log regressions for labour intensive sub-sectors

Sector	Year			
	1981 to 1990	1991 to 2001	2002 to 2011	2012 to 2023
Manufacturing (all)	0.357*** (0.023)	0.268*** (0.029)	0.188*** (0.028)	0.134* (0.064)
Textile & textile products	0.356*** (0.086)	-0.003 (0.036)	0.064 (0.066)	-0.090 (0.054)
Food products & beverages	0.230*** (0.017)	0.351*** (0.028)	0.104*** (0.022)	-0.221* (0.103)
Electrical & other equipment	0.471*** (0.053)	0.300*** (0.049)	0.446*** (0.048)	0.680*** (0.080)
Wood & wood products	-0.376*** (0.078)	0.230 (0.478)	-0.499*** (0.107)	-0.381*** (0.084)
Cement & other non-metallic minerals	0.162*** (0.012)	0.134*** (0.030)	0.379*** (0.060)	-0.172** (0.071)
Paper products, printing, & publishing	0.429*** (0.050)	0.206 (0.422)	0.096* (0.043)	0.474*** (0.107)
Gems, jewellery & miscellaneous	0.689** (0.222)	0.072** (0.019)	0.415*** (0.063)	0.144 (0.097)
Services (all)	0.514*** (0.010)	0.513*** (0.014)	0.378*** (0.015)	0.523*** (0.055)
Trade	0.769*** (0.025)	0.482*** (0.021)	0.288*** (0.022)	0.430*** (0.087)
Hotels and Restaurants	0.593*** (0.059)	0.424*** (0.019)	0.551*** (0.045)	0.370** (0.140)
Education	0.274*** (0.022)	0.511*** (0.036)	0.459*** (0.066)	0.376*** (0.048)
Health and Social Work	0.216*** (0.014)	0.556*** (0.015)	0.369*** (0.022)	0.768*** (0.070)
Financial Services	0.610*** (0.037)	0.219*** (0.051)	0.693*** (0.030)	0.707*** (0.079)
Transport and Storage	0.817*** (0.086)	0.676*** (0.019)	0.352*** (0.011)	0.557*** (0.028)

Source: RBI KLEMS, 2024; Authors' calculations.
Note: We estimate employment elasticity for the sub-sectors from 1980–81 to 2022–23. The sample period is divided into four broad time periods to illustrate the evolution of elasticity over time. Labour is defined as the number of persons employed (in '000s). Value added is in constant prices (2011-12) prices (Rs. crore). The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic. The standard errors are mentioned in parenthesis. The significance levels are denoted by ***, **, * for 1%, 5% and 10% levels, respectively.

2.3. Employment multiplier

While employment elasticity captures the responsiveness of job creation to output growth within a sector, it does not reflect the broader employment effects that arise through inter-sectoral linkages. As sectors expand, they create not only **direct employment** but also generate **indirect employment** in related industries. These indirect effects—often referred to as **employment multipliers**—emerge due to the interconnected nature of production and consumption across sectors.

Every industry is connected to other economic sectors through backward linkages, which involve suppliers providing necessary materials, and forward linkages, where workers spend their earnings. Beyond the direct employment an industry sustains, it also supports numerous indirect jobs. When industries with strong linkages experience job or output fluctuations, the effects ripple across multiple sectors.

To quantify these indirect effects, we estimate **employment multipliers** using the **Leontief inverse matrix** derived from input–output tables. The Leontief inverse captures how a unit increase in final demand in one sector affects output—and consequently employment—across the entire economy through production chains.

We hence calculate the **backward linkage employment multiplier** for each of the labour intensive sub-sectors identified in manufacturing and services. [7] This helps us identify sectors where demand-side investments can maximize employment gains with a higher multiplier indicating a greater number of additional jobs through strong inter-sectoral connections. In this way, employment multipliers complement elasticity estimates, offering a more comprehensive understanding of the job creation potential of different sectors.

2.3.1. Methodology

The Input-Output (I-O) framework models the inter-sectoral linkages within the economy and the values of inter-industry flows of goods and services. We utilize the 2018-19 I-O supply use table constructed by the Agriculture, Industry, Trade, Technology & Skills vertical of the National Council of Applied Economic Research (NCAER) of the same year in our analysis.

The National Statistical Office (NSO) releases Supply and Use Tables (SUT), which comprises of the Supply Table and the Use Table. The Supply Table presents details regarding the industry-wise supply of products in the economy. The Use Table provides details about the product used by the industries.

The 2018–19 Supply and Use Table contains data for 66 industries while the 2018-19 I-O table has 64 sectors. We collapse this 64-sector I-O table into a 27 sector I-O table to align with the

[7] Indirect employment, or employment multipliers, stem from three key factors: supplier effects, re-spending effects, and public sector employment effects. Supplier effects refer to the impact that job creation or loss in one industry has on its suppliers (Bivens, 2019, Bhandari et al., 2022).

classification used in the India KLEMS database. We compute the Leontief Inverse matrix using the I-O table for the year 2018-19 to estimate backward linkages. The Leontief inverse multiplied by the direct employment coefficient (defined as the ratio of employment to gross value of output) is used to estimate total employment including direct and indirect jobs. Direct employment refers to jobs generated within a sector due to its own economic activity, while indirect employment captures jobs created in backward-linked sectors. We use the indicator 'Number of persons employed (in '000s)' from the India KLEMS database, as the measure of direct employment.

Theoretical structure:

$$X_i = \sum_j X_{ij} + F_i$$

j = 1,2,3,….,n
Where,
X_i is the total output of i^{th} sector
X_{ij} is the total output of i^{th} sector consumed in j^{th} sector
F_i is the total final demand for the i^{th} sector consisting of private consumption

$$X_{ij} = a_{ij} X_j$$

Where, a_{ij} is the output of sector i used as input by sector j for producing one unit of output.
In Matrix notation:

$$(I - A)X = F$$
$$X = (I - A)^{-1} F$$

$(I - A)^{-1}$ is the Leontief inverse
Labour output ratio: $E_i = \frac{L_i}{X_i}$

Employment Multipliers: $L = \hat{E} * (I - A)^{-1}$

The total employment generated or jobs created by each sector was estimated by multiplying the sector's gross output[8] for the year 2018-19 with the corresponding employment multiplier, derived from the input-output analysis. Considering the Supply Use tables report information in current prices, we use current prices for the analysis pertaining to the I-O framework, to maintain consistency.

Using this methodology, we estimate the backward employment multiplier in the sub-sectors we classify as labour intensive (**Table 2.3**).

[8] We use gross output data from the India KLEMS database to estimate total employment and the number of direct jobs. This enables us to incorporate information up to the year 2022–23.

Table 2.3: Employment multiplier estimations for labour intensive sub-sectors

Sector	Backward linkage employment multiplier	No. of persons per Rs. 1 crore GVO (at current prices)
Manufacturing		
Textile & textile products	0.047	47
Food products & beverages	0.088	88
Electrical & other equipment	0.030	30
Wood & wood products	0.089	89
Cement & other non-metallic minerals	0.026	26
Paper products, printing, & publishing	0.036	36
Gems, jewellery & miscellaneous	0.043	43
Services		
Trade	0.042	42
Hotels and Restaurants	0.077	77
Education	0.022	22
Health and Social work	0.027	27
Financial Services	0.025	25
Transport and Storage	0.020	20

Source: Supply-Use table 2018-19; RBI KLEMS, 2024; Authors' calculations.
Note: i. We estimate employment multiplier for the sub-sectors using the I-O tables for the year 2018-19; ii. The variables used to estimate the employment multiplier are all in current prices, i.e. Gross value of output (GVO) and Intermediate inputs; iii. The number of persons employed is from RBI KLEMS database.

2.4. Projecting job creation

Using the employment elasticity and multiplier estimates, we simulate impacts on employment for each year until 2030, under two scenarios:

(1) increase in sectoral GVA with the sectoral employment elasticity fixed at current estimates, and

(2) increase in sectoral GO for given (backward) employment multiplier for sub-sectors

2.4.1 GVA growth for given elasticity for aggregate sectors

What would be the impact of higher GVA on employment creation in the labour intensive sectors? In this simulation, we induce varying scenarios of growth in the Gross Value Added, keeping the employment elasticity constant. We estimate the employment elasticity from KLEMS for the previous decade (2012 to 2023) and keep it fixed for the simulations.

We have three scenarios for the growth in the GVA[9]:

1. *Baseline growth scenario*: The average growth rate for the period 2012 to 2023 has been used to forecast GVA values for 2025 to 2030.

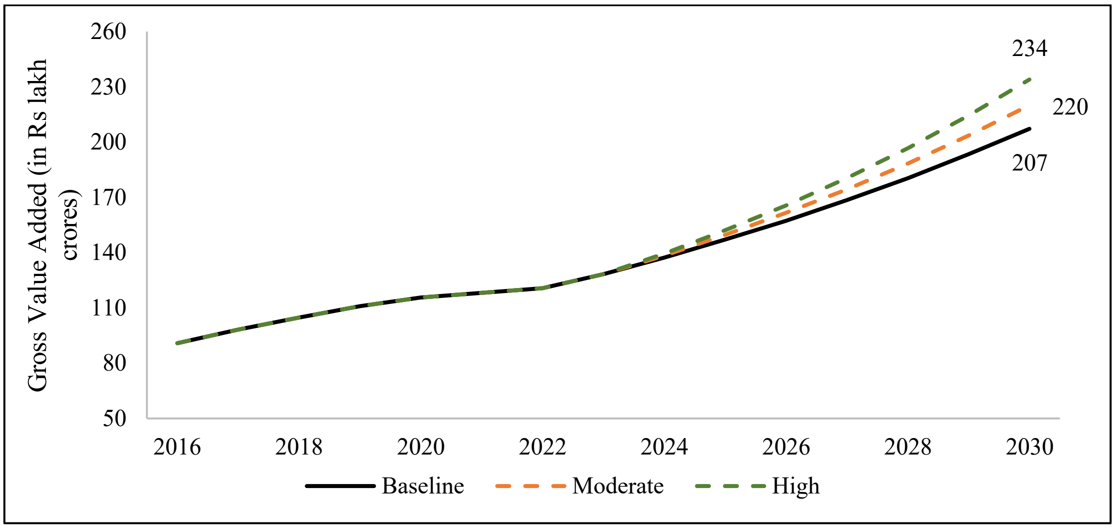
2. *Moderate growth scenario*: GVA growth rate in the moderate growth scenario includes an addition of 0.5 of the standard deviation of GVA growth rate from 2012 to 2023. The GVA values are forecasted for 2025 to 2030 using this modified GVA growth rate.

3. *High growth scenario*: GVA growth rate in the high growth scenario includes an addition of 1 of the standard deviation of GVA growth rate from 2012 to 2023. The GVA values are forecasted for 2025 to 2030 using this modified GVA growth rate.

To estimate projected growth rates of GVA, we assume that sectoral shares of GVA are constant and agriculture's GVA grows at baseline growth rate across scenarios. Next, we undertake the following steps to estimate the total economy-wide GVA by summing up these GVA values (at baseline, additional 0.5 SD under moderate and 1 SD increase under high growth scenarios in manufacturing and services GVA, keeping agriculture GVA constant) up to arrive at the overall GVA values across the three sectors to estimate each GVA series' growth rate (**Figure 2.2**). Since Agriculture, Manufacturing, and Services together account for a significant share of total GVA (Around 86.7% in 2023; Agriculture: 15.35%, Manufacturing: 16.92% and Services: 54.4%), their individual growth paths have substantial influence on the overall GVA and, by extension, GDP growth. While *Viksit Bharat* focuses on the path till 2047, these projections provide insights into the trajectory required to achieve the goal of at least 8% GDP growth rate, with focus on period up to 2030 (**Table 2.4**).

[9] The year 2020-21 has been dropped when estimating the average growth rate for the period under consideration.

Figure 2.2: Total GVA projections



Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. GVA values are in constant 2011-12 prices. ii. The actual data used project GVA spans from 2011 to 2023; iii. Data for 2021 has been dropped to account for distortions caused by COVID.

Table 2.4: Total GVA growth rate (%)

Year	Baseline growth scenario	Moderate growth scenario	High growth scenario
2024	6.995	7.904	8.813
2025	7.024	7.938	8.864
2026	7.053	7.970	8.912
2027	7.081	8.002	8.959
2028	7.109	8.033	9.004
2029	7.137	8.062	9.047
2030	7.164	8.091	9.089

Source: Authors' calculations.
Note: GVA values are in constant 2011-12 prices (Rs. Crores)

Our estimates indicate that if manufacturing and services sectors grow at 8.2% and 9.0%, respectively, overall GVA annual growth of 8% can be achieved. This represents the **moderate growth scenario**, where 0.5 standard deviations are added to the average growth rate for the period 2012 to 2023. GVA can grow at higher growth rate, i.e. around 9%, if manufacturing sector grows at 10.7% and services sector at 9.6%. This is considered the **high growth**

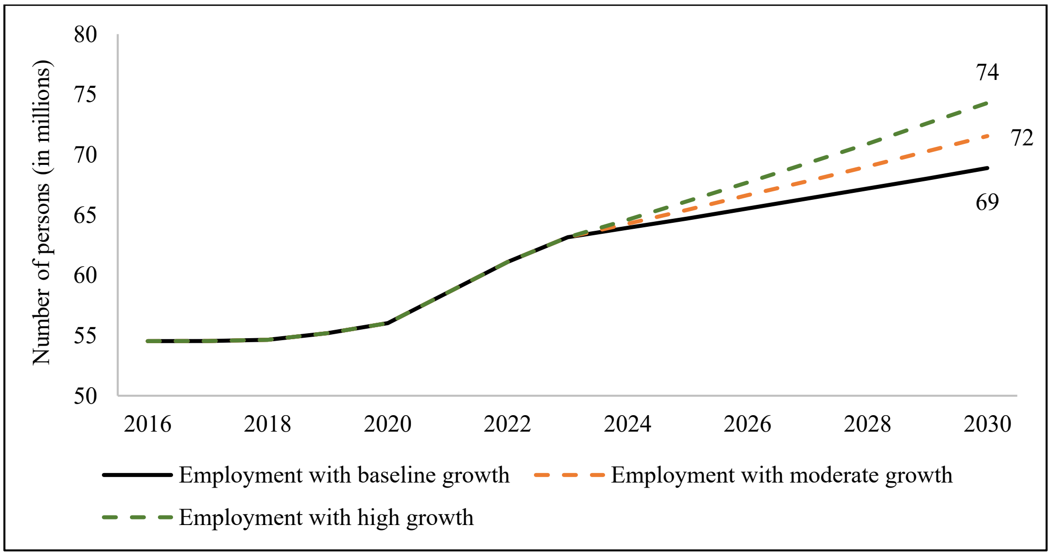
scenario, where a one SD increase occurs in the average growth rate for the period under consideration.

If the *Viksit Bharat* agenda is effectively implemented, with policies aimed at enhancing sectoral GVA growth, achieving 8% GVA growth could lead to significant employment generation across sectors, as shown in the following sections. [10]

A. Manufacturing sector simulations

The Gross value added (at 2011-12 prices) of the total manufacturing sector as of 2023 was Rs. 25,04,663.330 crore. The GVA grew at 5.7% on an average during the period 2012 to 2023. In the moderate growth scenario, the GVA of manufacturing sector will grow at 8.2% and at 10.7% in the high growth scenario. Using the GVA from these three scenarios, the number of persons employed is estimated using the CAGR method of employment elasticity.

Figure 2.3: Projected employment in the manufacturing sector



Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. Labour is defined as the number of persons employed (in millions) and the gross value added is in constant prices (2011-12) prices (Rs., crore); ii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic; iii. Data used to project GVA spans from 2012 to 2023.

In the baseline growth scenario, the projected number of persons employed is 68,889 thousand. The projection for number of persons employed in the moderate growth scenario is 3.9 %

[10] Since GDP = GVA + Taxes on Products - Subsidies on Products, under the naïve assumption of no change in net tax revenue, we get a lower bound on the growth in GDP of 8% and higher growth rate in the high growth GVA scenario.

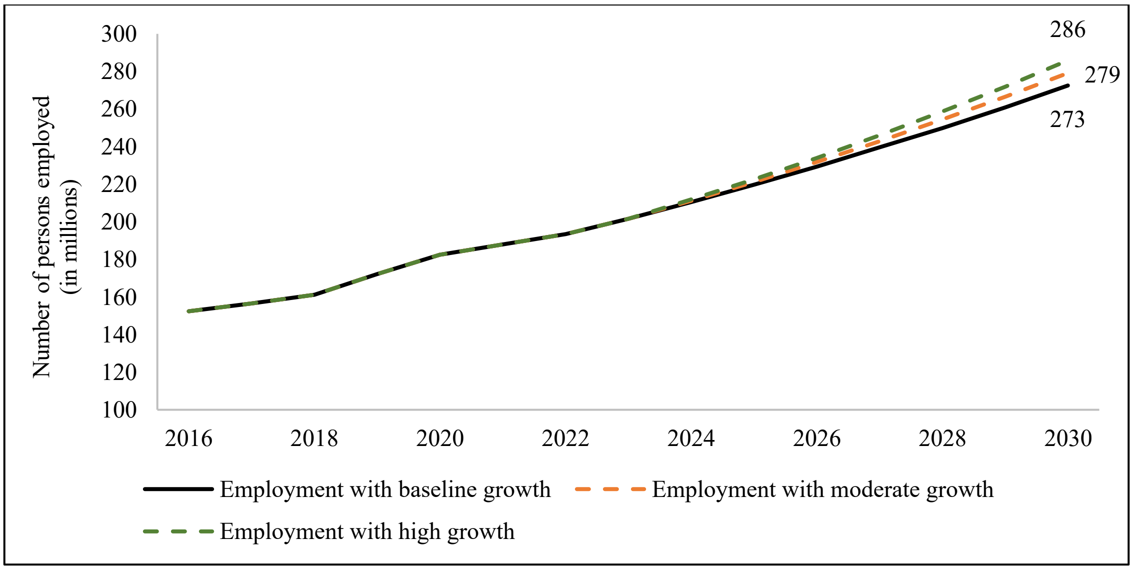
higher than the baseline scenario, at 71,544 thousand persons. In the high growth scenario, it is 7.8 % higher than employment in baseline scenario (**Figure 2.3**).

B. Services sector simulations

The gross value added (constant 2011-12 prices) of the services sector as of 2023 is Rs. 8,058,501.245 crore. The GVA grew at 8.3% on an average during the period 2011-12 to 2023. In the moderate growth scenario, the GVA of services sector will grow at 9.0% and at 9.6% in the high growth scenario.

From **Figure 2.4** we observe that in the services sector, 272,518 thousand persons are projected to be employed by 2030 with the baseline GVA growth. The projected number of persons employed increases by 2.4% to 2,79,130 thousand with moderate GVA growth. It increases by 4.9% to 285,880 thousand with high GVA growth.

Figure 2.4: Projected employment in the services sector



Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. Labour is defined as the number of persons employed (in millions) and the gross value added is in constant prices (2011-12) prices (Rs. crore); ii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic; iii. Data used to project GVA spans from 2012 to 2023.

Overall, the projected employment under the moderate and high growth scenarios are as shown in **Table 2.5** below.

Table 2.5: Projected employment with moderate and high GVA growth

	Manufacturing		Services	
Year	Employment with moderate GVA growth	Employment with high GVA growth	Employment with moderate GVA growth	Employment with high GVA growth
2025	65	66	221	223
2026	67	68	232	234
2027	68	69	243	246
2028	69	71	254	259
2029	70	73	266	272
2030	72	74	279	286

Source: Authors' calculations.
Note: Employment refers to number of persons employed (in millions). GVA is in 2011-12 constant prices (Rs crores)

Relative to the baseline scenario, employment in the overall manufacturing sector would increase by 3.9% under the moderate growth scenario and 7.8% in the high growth scenario. In the services sector, on the other hand, the increase would be of 2.4% and 4.9%, respectively.

The employment elasticity estimates, however, give us a conservative projection of the potential of employment creation since they do not take into account the multiplier effects that can be created through inter-sectoral linkages. In the next section, therefore, we project the impact of increase in Gross Output of the relatively more labour intensive sub-sectors on job creation through inter-sectoral linkages.

2.4.2. Changing the GO for given (backward) multiplier for sub-sectors

In this simulation, we induce changes to the Gross Output (GO), keeping the (backward) employment multiplier for 2018-19 constant, i.e. we assume that the employment multiplier does not change.

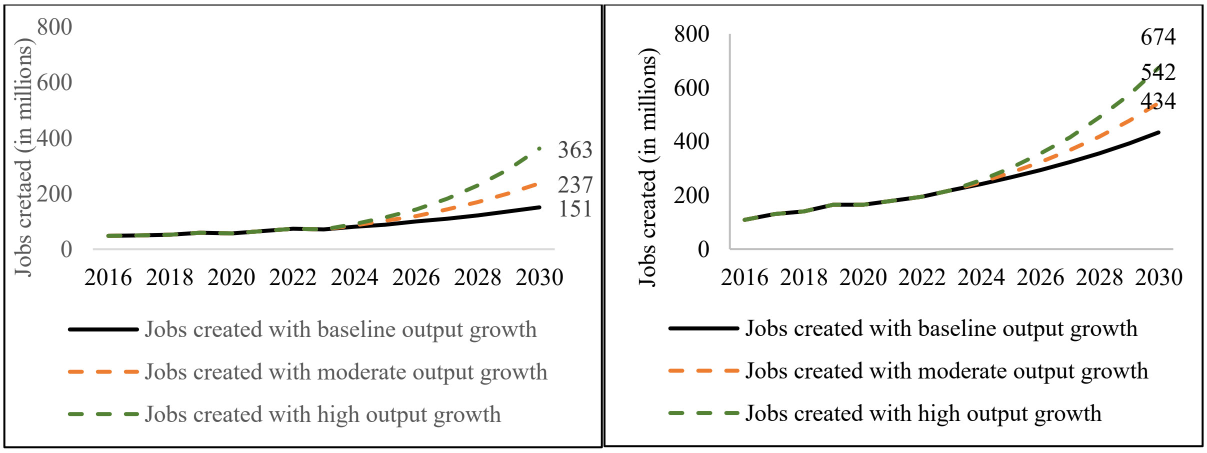
1. *Baseline growth scenario*: The average growth rate for the period 2012 to 2023 has been used to forecast GO values for 2025 to 2030.
2. *Moderate growth scenario*: GO growth rate in the moderate growth scenario includes an addition of 0.5 of the standard deviation of GO growth rate from 2012 to 2023. The GO values are forecasted using this modified GO growth rate.
3. *High growth scenario*: GO growth rate in the high growth scenario includes an addition of 1 of the standard deviation of GO growth rate from 2012 to 2023. The GO values are forecasted using this modified GO growth rate.

The employment multiplier is multiplied with the GO for the three scenarios to arrive at the aggregate number of jobs created for each scenario from the expansion of each labour intensive sub-sector.[11]

A. Manufacturing labour intensive sub-sectors

The Gross Output for textiles industry as of 2023 is Rs. 1,534,041 crores. The gross output grew at 11.1% on an average from 2012 to 2023. This growth rate has been considered to construct the baseline scenario. In the moderate growth scenario, gross output is expected to grow at 18.5%, and at 25.9% in the high growth scenario.

Figure 2.5: Projected job creation (manufacturing multiplier)



(a) Textiles & textile products **(b) Food products & beverages**

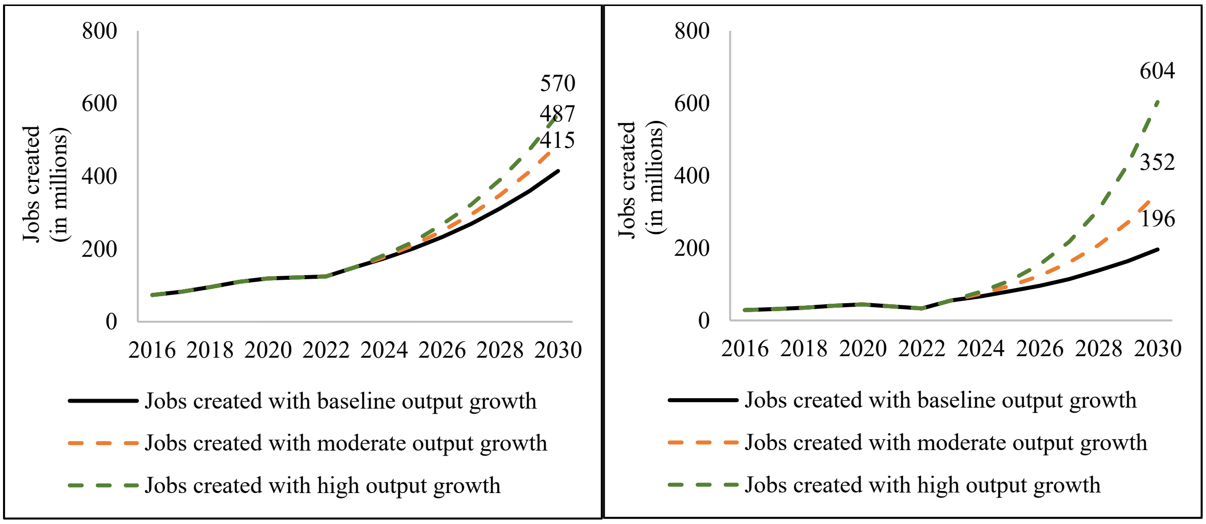
Source: Supply-Use table 2018-19; RBI KLEMS, 2024; Authors' calculations.
Note: i. The period of analysis is from 2012 to 2023; ii. The gross output is in current prices; iii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic.

In the baseline scenario, gross output grows at the rate of the average growth rate for the period 2012 to 2023. As a result, the cumulative number of jobs created through increased output of the textile, leather and footwear industry, is projected at 150,704 thousand by the year 2030. The projected number of aggregate economy-wide jobs created in the moderate and high growth scenario increase by 57% and 140%, respectively, relative to the baseline growth scenario (**Figure 2.5**).

[11] The year 2020-21 has been dropped when estimating the average growth rate for the period under consideration.

B. Services labour intensive sub-sectors

Figure 2.6: Projected job creation (services multiplier)



(a) Trade **(b) Hotels and Restaurants**

Source: Supply-Use table 2018-19, RBI KLEMS, 2024; Authors' calculations.
Note: i. The period of analysis is from 2012 to 2023; ii. The gross output is in current prices; iii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic.

Similarly, taking into account the employment multiplier in the two most labour intensive sub-sectors (i.e. Trade and Hotels, restaurants) in services, we estimate that the total number of aggregate, economy-wide jobs created by 2030 would increase by 18% – 79% with moderate increase in gross output of these services sub-sectors and 37% – 200% in the high growth scenario (**Figure 2.6**).

2.5. Summary

The simulation exercises indicate that increasing investment in the labour intensive manufacturing and services sub-sectors can lead to doubling of employment in the aggregate economy, if we take into account the inter-sectoral linkages of these labour intensive sub-sectors. We summarize the policy implications later in Section 4.

3. Unleashing the supply of quality labour

We now turn the labour supply constraints in the Indian economy, which emphasize the need to increase labour productivity for gainful employment, particularly due to the increasing capital intensity of production.

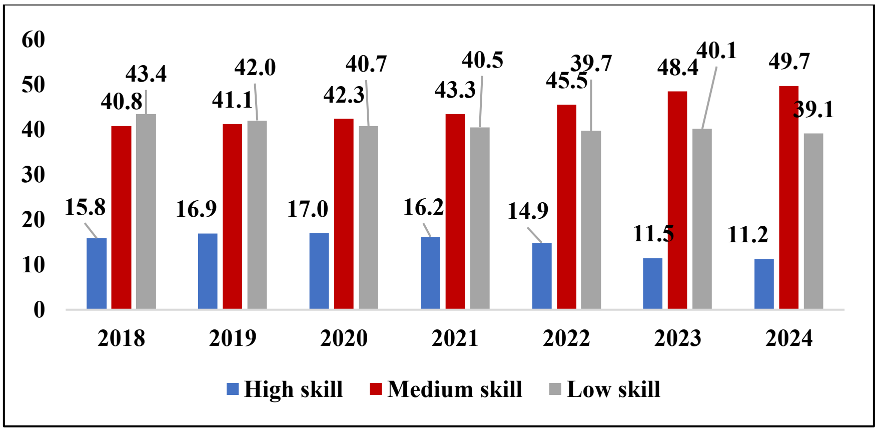
3.1 Demand for skills

3.1.1 Skill distribution in aggregate economy

As shown in **Figure 3.1**, low-skill employment accounted for the largest share of total employment in 2017–18 (2018, henceforth). [12] Over time, the share of both low-skill and high-skill employment has declined, while the share of medium-skill employment has increased. The share of medium-skill employment rose from 40% in 2018 to nearly 50% in 2024, making it the largest contributor to total employment in that year.

In addition to having the highest share of total employment, medium-skill employment also recorded the highest year-on-year growth among all skill categories since 2020. However, between 2023 and 2024, the growth rate of medium-skill employment declined, while the growth in high-skill employment increased.

Figure 3.1: Employment distribution and employment trends by skills for workers aged 15-59 years (%)



Source: PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. Manufacturing sector includes 2-digit industry codes from 10 to 33 and Services sector includes 2-digit industry codes from 45 to 99; ii. Skill categorization is based on NCO (1-digit level). Weighted sample size varies from 341 million in 2017-18 to 475 million in 2023-24.

[12] Skill categorization is based on the first-digit classification of National Classification of Occupations (NCO) codes. The following classifications have been used: **High-skilled:** Legislators, Senior Officials, and Managers; Professionals; and Associate Professionals; **Medium-skilled:** Clerks; Service Workers and Shop & Market Sales Workers; Skilled Agriculture and Fishery Workers; **Low-skilled:** Craft and Related Trades Workers; Plant and Machine Operators and Assemblers; and Elementary Occupations; for skill classification, throughout we use the sample of 15 – 59-year-olds.

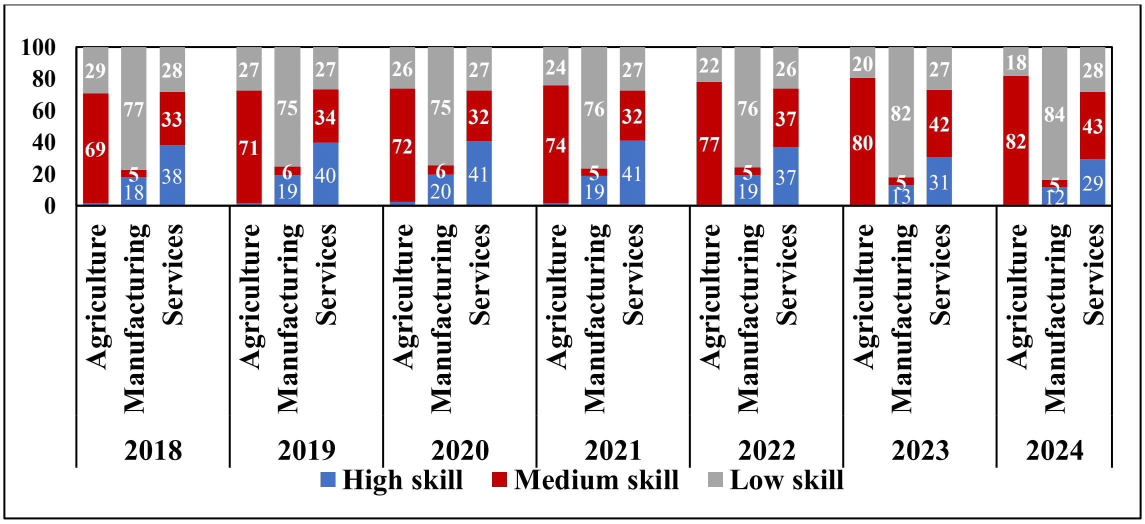
3.1.2. Sectoral skill distribution

Sector-wise skill distribution indicates that the manufacturing sector continues to be dominated by low-skilled workers, who accounted for 84% of total manufacturing employment in 2024. In contrast, the agriculture and services sectors are dominated by medium-skilled employment, comprising 82% and 43% of their respective workforces in 2024. High-skill employment is primarily concentrated in the services sector, where it accounted for 29% of employment in 2024 (**Figure 3.2**).

The share of medium-skill employment has increased significantly in agriculture—from 69% in 2017–18 to 82% in 2023–24—and in services, from 33% to 43% over the same period. In the manufacturing sector, the share of medium-skill employment has remained largely unchanged. Meanwhile, the share of high-skill employment has declined in both the manufacturing and services sectors: from 18% to 12% in manufacturing, and from 38% to 29% in services between 2018 and 2024. The share of low-skill employment has decreased in agriculture (from 29% to 18%), remained relatively stable in services (around 28 %), but increased in manufacturing (from 77% to 84%).

Year-on-year employment growth in the agriculture and services sectors has been highest for medium-skill jobs (except in 2023-24 where low skill employment showed the highest growth). Within manufacturing, low-skill employment has shown the highest growth for last two years. Although high-skill employment declined across all three sectors from 2018 to 2023, it began to rise again between 2023 and 2024.

Figure 3.2: Employment distribution by skills (%)

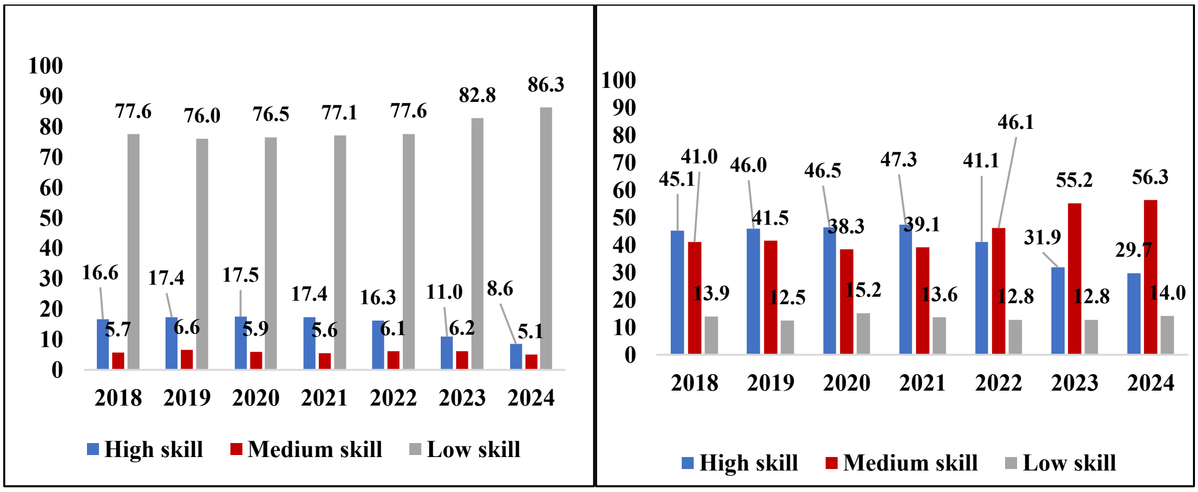


Source: PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. Agriculture sector includes 2 digit industry codes from 01 to 03; Manufacturing sector includes 2 digit industry codes from 10 to 33 and Services sector includes 2 digit industry codes from 45 to 99; ii. Skill categorization is based on NCO (1-digit level). iii. The weighted sample size in Agriculture varies from 143.98 million in 2017-18 to 207.41 million in 2023-24, in Manufacturing it varies from 42.65 million in 2017-18 to 57.06 million in 2023-24, and in Services from 109.29 million in 2017-18 to 146.95 million in 2023-24.

3.1.3. Skill distribution within labor-intensive sectors

As per **Figure 3.3**, labour-intensive manufacturing sector is dominated by low skilled employment. However, labour-intensive services sector is dominated by medium skilled workers.

Figure 3.3: Employment distribution by skills within labour- intensive sectors for workers aged between 15-59 years (%)



(a) Labour-intensive manufacturing **(b) Labour-intensive services**

Source: PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data in Section 2; ii. For labour-intensive manufacturing, the weighted sample size varies from 19.95 million in 2017–18 to 25.04 million 2023–24 and for labour-intensive services it varies from 57.68 million in 2017-18 to 79.55 million in 2023-24.

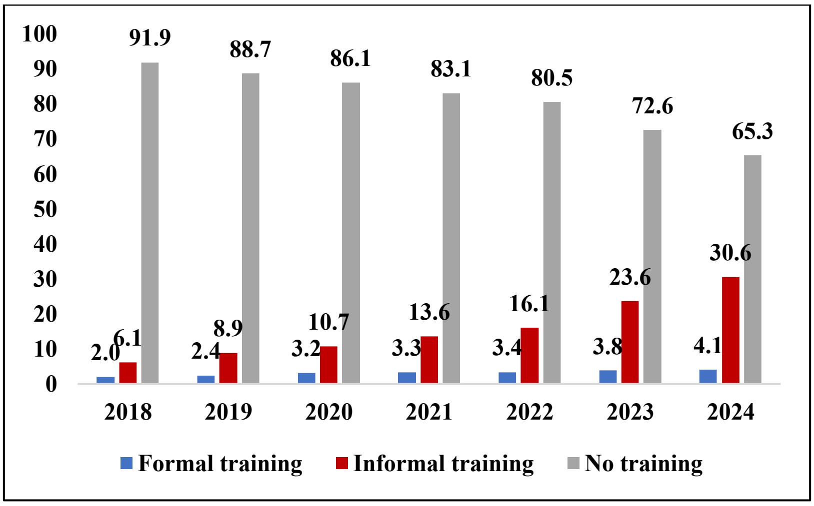
Year-on-year employment growth in labour-intensive services is mostly the highest for medium-skilled workers. However, in 2024, growth was higher for low-skilled employment within labour-intensive services. In labour-intensive manufacturing, low-skilled workers recorded the highest employment growth.

3.2. Supply of skills

3.2.1 Supply of skills in aggregate economy

There has been a decline in the share of untrained workers over time. In 2018, 92% of workers had no training, which fell to 65% by 2024. However, the majority of workers remain untrained. As of 2024, only 4% of workers had received formal training. Moreover, the year-on-year growth in the number of formally trained workers is lower than the growth in the number of informally trained workers (**Figure 3.4**).

Figure 3.4: Distribution of workers aged 15-59 years by training (%)

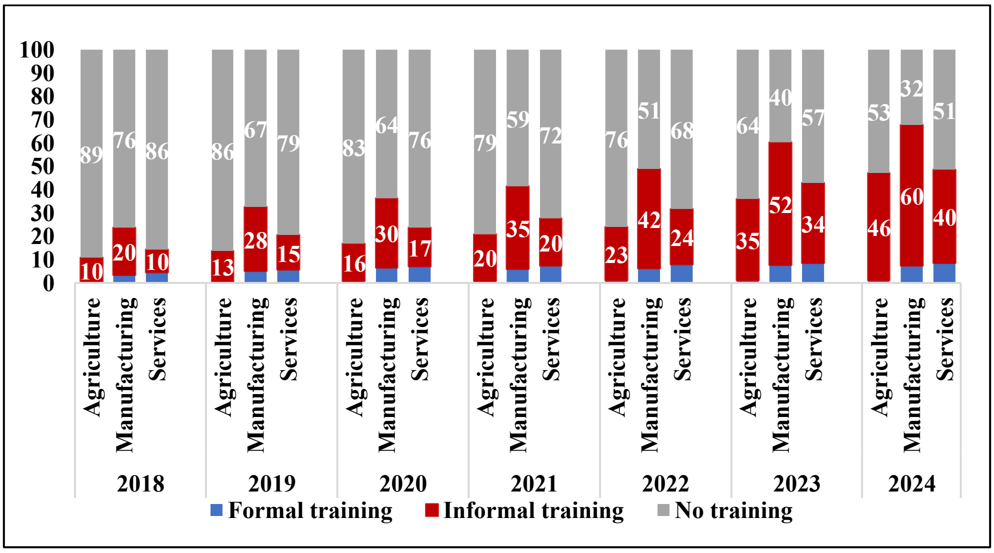


Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. Informal training includes hereditary, self-learning, learning on the job and other types of training; ii. Weighted sample size varies from 688 million in 2017-18 to 765 million in 2023-24.

3.2.2. Sectoral supply of skills

Figure 3.5 shows that agriculture and services sectors are dominated by workers who have not received any training, followed by those who have received informal training. Manufacturing sector is dominated by workers who have received informal training. A negligible proportion of workers have formal training within Agriculture. The share of workers who have received formal training is highest among the services sector at 8.7%.

Figure 3.5: Workforce distribution by training within sectors (%)



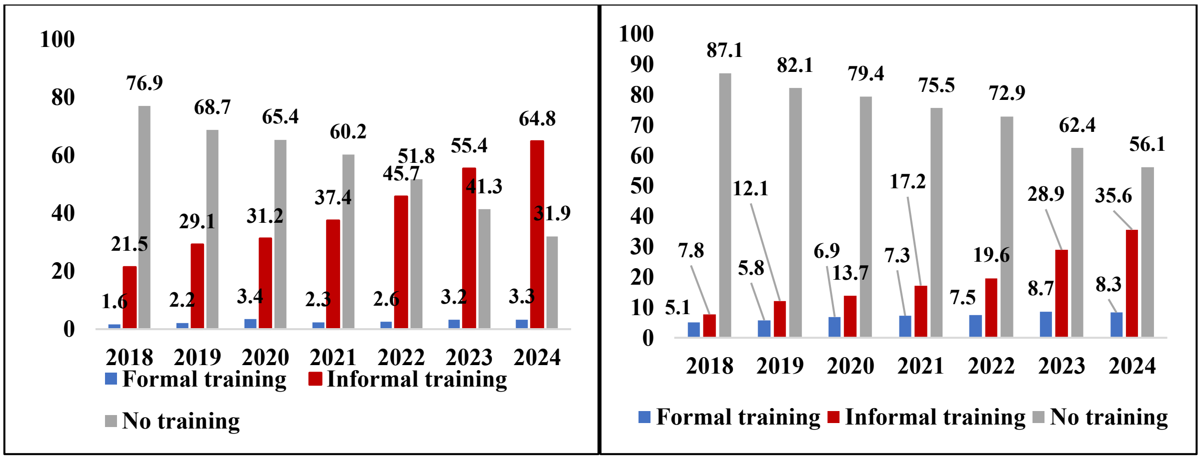
Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. Agriculture sector includes 2-digit industry codes from 01 to 03; Manufacturing sector includes 2-digit industry codes from 10 to 33 and Services sector includes 2-digit industry codes from 45 to 99; ii. Informal training includes hereditary, self-learning, learning on the job and other types of training; iii. Weighted sample size within agriculture varies from 143 million in 2017-18 to 207 million in 2023-24; weighted sample size within manufacturing varies from 43 million in 2017-18 to 57 million in 2023-24; weighted sample size within services varies from 109 million in 2017-18 to 147 million in 2023-24.

The year-on-year growth in number of informally trained workers is higher than the growth in the number of formally trained workers in all three sectors.

3.2.3 Supply of skills within the labour- intensive sectors

The labour-intensive services sector is dominated by untrained workers. Labour intensive manufacturing is dominated by informally trained workers (**Figure 3.6**).

Figure 3.6: Workforce distribution by training within labour- intensive sectors for age group 15-59 years (%)



(a) Labour-intensive manufacturing **(b) Labour-intensive services**

Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. For labour-intensive manufacturing, the sample size varies from 19.95 million in 2017–18 to 25.08 million 2023–24 and for labour-intensive services it varies from 57.68 million in 2017-18 to 79.55 million in 2023-24.

The year-on-year growth in the formally trained workforce is lower than that of the informally trained workforce, within both manufacturing and services labour-intensive sectors, as of 2024. Moreover, the overall growth in trained individuals has declined between 2023 and 2024, in both labour-intensive sectors.

3.3. Demand and supply mismatch

Section 3.1 shows that most employment is being generated in medium-skill industries. Section 3.2 highlights that India has a relatively small proportion of trained workers, particularly those with formal training. However, as the economy evolves and the demand for high-skilled employment increases, it will be crucial to expand the share of trained workers, especially those who are formally trained.

Cross-country data from the ILO (as mentioned in Section 1) suggest a positive association between the share of trained workers and the share of high-skill employment, alongside a negative association with both medium- and low-skill employment. These data indicate that economies with a greater proportion of trained individuals tend to have a higher incidence of high-skill jobs. Additionally, India lies below the fitted regression line in the scatter plot of trained workers versus high-skill employment. This divergence implies that merely increasing the number of workers with some form of training is insufficient. As section 3.2. showed much of the existing training in India is informal which may limit its effectiveness in improving high skilled employment.

3.3.1 Estimated impact of skill training on employment

To assess the *impact of training on employment outcomes in India*, we estimate a logit regression model at the individual worker level using Periodic Labour Force Survey (PLFS) data for 2024. The analysis is restricted to young workers aged 15 to 29 years, who represent the segment of the population transitioning into the workforce.

$$Log\left[\frac{P(employed_{it})}{1-P(employed_{it})}\right] = \beta_o + \beta_1 training_{it} + \beta_2 gender_i + \beta_3 age_{it} + \beta_4 geduc_{it} + \beta_5 technedu_{it} + \beta_6 location_{it} + \gamma_s + \delta_t + \varepsilon_{it} \quad (3.1)$$

$employed_{it}$ is binary variable that takes value 1 if worker i is employed at time t and 0 if he is unemployed. Specifically, in regression 1 it takes value 1 if worker is employed in any job, in regression 2 it takes value 1 if worker is engaged in regular job and in regression 3 it takes value 1 if the worker is employed in a high skilled job in regression 3.

$trainingcategories_{it}$ takes value 2 if worker has formal vocational training, 1 if the worker has informal vocational training and 0 if the worker has no training;

$gender_{it}$ is variable that takes value 1 for a male worker and 2 for female worker;

age_{it} is continuous variable indicating the age of the worker;

$geduc_{it}$ is the categorical variable that indicates general education for worker i at time t: below primary, above primary, above secondary;

$technedu_{it}$ is the categorical variable that indicates technical education for worker i at time t: below graduate, above graduate level.

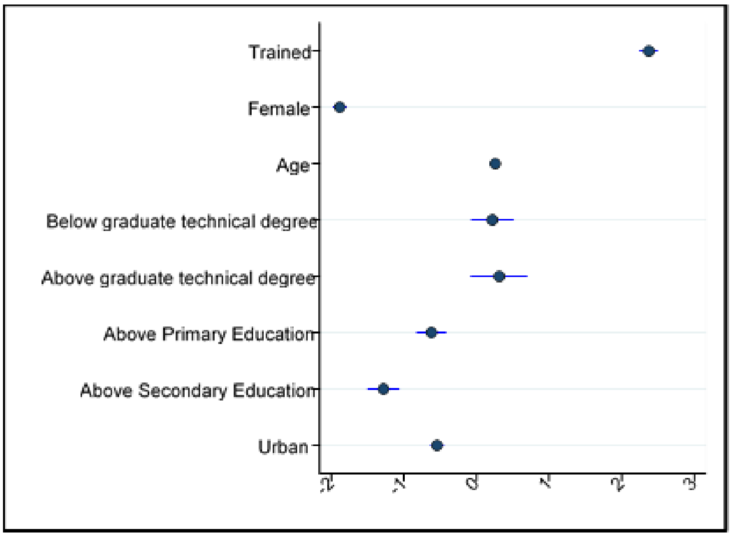
$location_{it}$ is the binary variable indicating urban/ rural location of worker i at time t;

γ_s are the state fixed effects;

ε_{it} is the error term.

Figure 3.7 shows the log-odds of being employed in any job, as estimated by logistic model equation 3.1.

Figure 3.7: Log (Odds) of being employed in any job in 2024 for workers aged 15-29 years

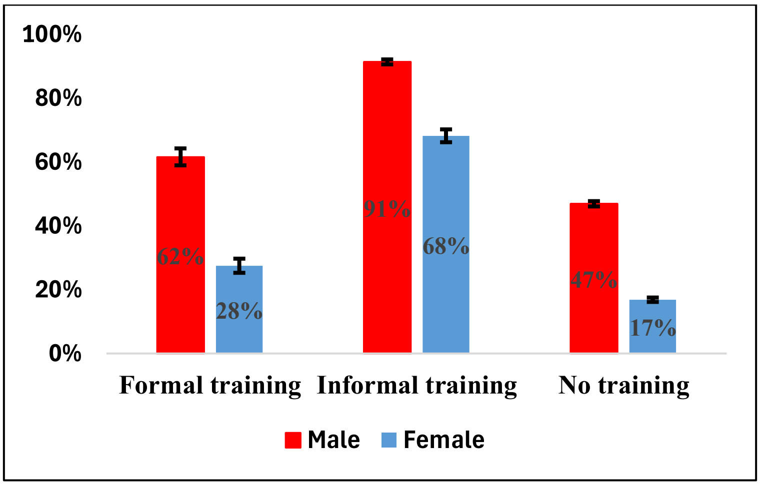


Source: PLFS (2023-24); Authors' calculations
Note: i. Log (Odds) is based on a logit regression regression based on PLFS data (2017–18 to 2023–24) that regresses whether the worker is employed in any job on whether the worker is trained, years of general education, types of technical education received by worker, age, location(rural/urban) and state fixed effects, for workers aged 15 to 29 years; ii. Coefficients are plotted with 99 percent confidence bands; iii. The weighted number of observations for the regression is 109,048.

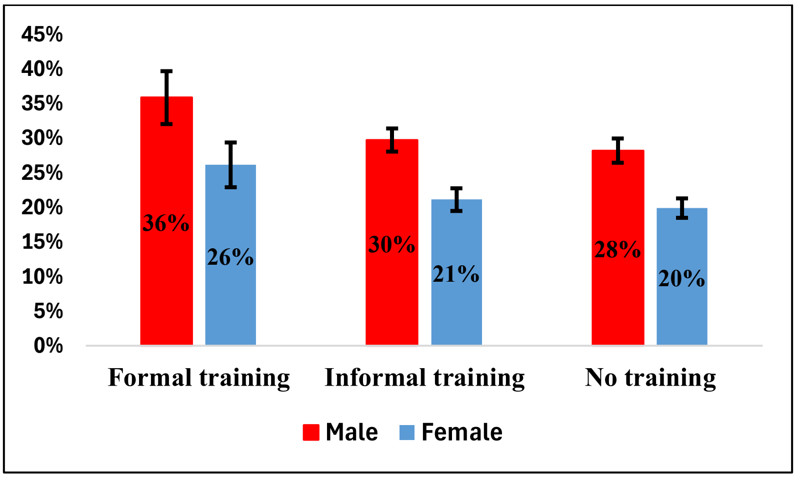
Figure 3.7 shows that having vocational training and technical education is positively associated with odds of being employed. Among these, vocational training shows the strongest and most statistically significant effect on the likelihood of being employed.

To further assess the importance of training, marginal effects are calculated at the mean values of the other explanatory variables to estimate the predicted probabilities of being employed across different categories of training. **Figure 3.8** presents the predicted probabilities of being employed in any job, in a regular salaried job, and in a high-skill job, based on training status.

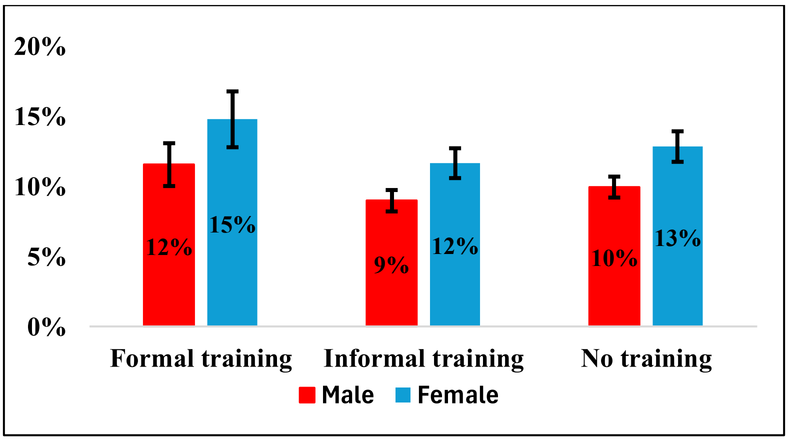
Figure 3.8: Predicted probability of being employed based on training level of worker aged 15 to 29 years (%)



(a) Employed in any job



(b) Employed in regular jobs



(c) **Employed in high-skilled job**

Source: PLFS (2023-24); Authors' calculations.

Note: i. Predicted probabilities are based on logit regressions using PLFS 2023–24 data for individuals aged 15–29 years; ii. Employment is coded as 1 if the person is employed and 0 if unemployed or out of the labour force. Regular job employment is coded as 1 if employed in regular jobs and 0 if casual or self-employed. High-skilled employment is coded as 1 if employed in high-skilled jobs and 0 if in low or medium-skilled jobs; iii. All regressions control for training type, general and technical education, age, location and state fixed effects; iv. The weighted sample size is 109,048 for overall employment, and 43,797 for regular and high-skilled employment regressions; v. 99% confidence intervals are shown on the bars.

The results show that workers with any form of vocational training have a higher likelihood of being employed compared to those without training. These results hold after controlling for education, gender, and location. The probability of being employed in regular salaried positions increases significantly for those with formal training. Informal training, by contrast, shows only a modest impact in this category. Additionally, it is seen that workers with formal training have a significantly higher predicted probability of being employed in high-skill occupations. This reinforces the importance of formal training programs that align with evolving skill demands. These results suggest that while any training is better than none, it is formal training that meaningfully improves employment outcomes—especially in better-quality, high-skill jobs.

3.4 Projections of the impact of increased formal vocational training on employment

3.4.1 Methodology

The simulations are based on a logit regression estimated at the worker level using PLFS data for workers aged 15 to 59 years over the period 2017–18 to 2023–24. The specification is as follows:

$$Log\left[\frac{P(employed_{it})}{1-P(employed_{it})}\right] = \beta_o + \beta_1 formaltraining_{it} + \beta_2 gender_i + \beta_3 age_{it} + \beta_4 geduc_{it} + \beta_5 techedu_{it} + \beta_6 location_{it} + \gamma_s + \delta_t + \varepsilon_{it} \quad (3.2)$$

Where

For projecting employment for labour-intensive manufacturing, $employed_{it}$ takes value 1 if the worker is employed in the manufacturing sector, and 0 if the worker is unemployed. For projecting employment for labour-intensive services, $employed_{it}$ equals 1 if the worker is employed in the services sector, and 0 if the worker is unemployed. For projecting employment for labour-intensive sector (including both manufacturing and services), $employed_{it}$ equals 1 if the worker is employed in either manufacturing or services and 0 if the worker is unemployed.

$formaltraining_{it}$ takes value 1 if worker has received formal vocational training and 0 otherwise;

$gender_{it}$ is variable that takes value 1 for a male worker and 2 for female worker;

age_{it} is continuous variable indicating the age of the worker;

$geduc_{it}$ is the categorical variable that indicates general education for worker i at time t: below primary, above primary, above secondary;

$techedu_{it}$ is the categorical variable that indicates technical education for worker i at time t: below graduate, above graduate level.

$location_{it}$ is the binary variable indicating urban/ rural location of worker i at time t;

γ_s are the state fixed effects;

δ_t are the time fixed effects;

ε_{it} is the error term.

Using regression equation (3.2), the simulation estimates how increases in the share of formally trained workers affect employment in labour-intensive manufacturing, labour-intensive services sector and labour-intensive sector as a whole over the six-year period from 2025 to 2030, taking 2024 as the base year. Specifically:

- The marginal effect of formal training on employment is estimated, reflecting the average change in the probability of being employed in manufacturing, the service sector, or in either of the two sectors, associated with one additional trained worker, holding other characteristics constant.
- This marginal effect (denoted as **Δ**) is then used to estimate changes in total employment under hypothetical scenarios. The scenarios are identified based on changing either the share of formally trained workers in the workforce or the marginal effect obtained from logit model.

The projected change in employment is calculated using the following formula:

$$employment_{t+n} = employment_t + \left(\Delta_{t+n} \times \left(\mathrm{N}_{t+n} \times (Sharetrained_{t+n} - Sharetrained_t)\right)\right) \qquad (3.3)$$

Where:

- $employment_{t+n}$ is the projected employment in year t+n
- $employment_t$ is the actual employment in base year t
- Δ_{t+n} is the marginal effect period under different scenarios in t+n period
- N_{t+n} refers to the size of the relevant workforce under various scenarios in time t+n.
- $Sharetrained_{t+n} - Sharetrained_t$ is the assumed increase in the share of workers with formal vocational training between year t+n and base year t, under various scenarios.

Simulation scenarios: Based on varying growth of share of formally trained workers

1. **Baseline**: It is assumed that the y-o-y growth in the number of formally trained workers and the number of total workers is the same as the average y-o-y growth from 2018 to 2024 (excluding 2020-21), in each of the projected years from 2025 to 2030.
2. **Moderate increase in the number of formally trained workers:** It is assumed that the y-o-y growth in the number of formally trained workers is 0.5 SD greater than the average y-o-y growth in the number of formally trained workers and the number of total workers is the same as the average y-o-y growth from 2018 to 2024 (excluding 2020-21), in each of the projected five years from 2025 to 2030.
3. **High growth in number of formally trained workers**: It is assumed that the y-o-y growth in the number of formally trained workers is 1 SD greater than the average y-o-y growth in the number of formally trained workers and the number of total workers is

the same as the average y-o-y growth from 2018 to 2024 (excluding 2020-21), in each of the projected five years from 2025 to 2030.

3.4.2 Employment impacts in labour-intensive manufacturing sector

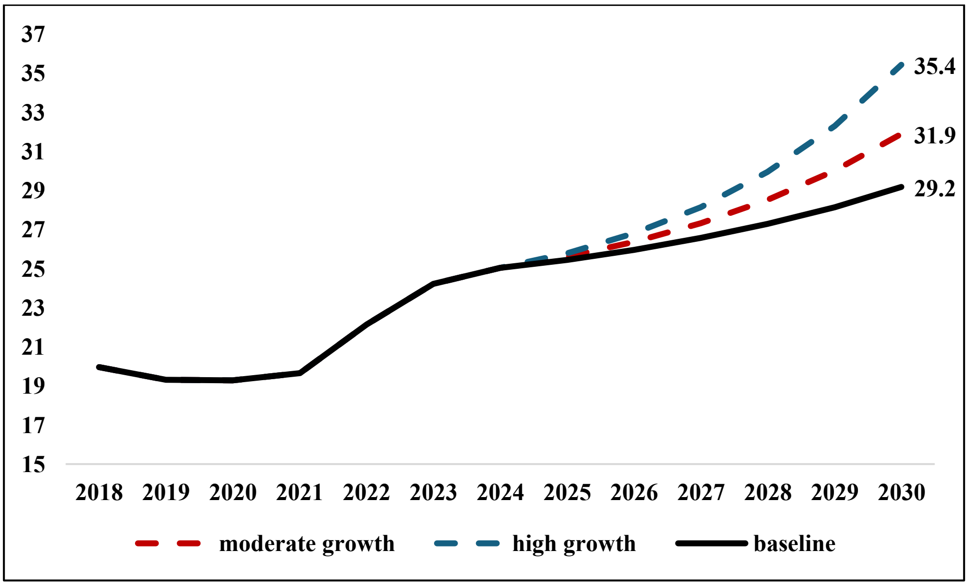
As of the base year 2024, the number of employed persons in labour intensive manufacturing stands at 25 million. **Figure 3.9** and **Table 3.1** shows the following results of the simulations:

- **Under the baseline scenario**, the share of formally trained workers is projected to increase from 4% to 9% (a rise of 5 pp points) by 2030. The addition to the number of jobs in labour-intensive manufacturing is expected to be around 4.1 million relative to the base year (column 4 of Table 3.1). This represents a 16.6% increase in employment compared to 2024, within labour-intensive manufacturing (column 5 of Table 3.1).

- **Under the moderate growth scenario**, the share of formally trained workers is projected to rise from 4% in 2024 to 13% by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 6.8 million relative to the base year (column 4 of Table 3.1) representing a 27.4% increase, within labour-intensive manufacturing (column 5 of Table 3.1).

- **Under the high growth scenario**, the share of formally trained workers is projected to rise from 4% in 2024 to 16% by 2030 (a rise of 12 pp points). The cumulative addition to jobs is projected to be around 10.3 million (column 4 of Table 3.1), representing a 41.5% increase over the base year (column 5 of Table 3.1).

Figure 3.9: Employment in labour-intensive manufacturing (ages 15–59) under different scenarios (millions)



Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,027,493 observations. The model regresses binary indicator on whether worker is employed in manufacturing sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Simulated employment gains under baseline, moderate, and high-growth scenarios in formal training reflect the potential impact of increasing the share of formally trained workers between 2024–25 and 2029–30; iv. Employment numbers are presented in millions.

Table 3.1: Cumulative addition to jobs in labour intensive manufacturing under different scenarios

Scenario	Employment in labour intensive manufacturing in 2024 (millions)	Employment in labour intensive manufacturing in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	25.0	29.2	4.1	16.6	4	9
Moderate Growth	25.0	31.9	6.9	27.4	4	13
High Growth	25.0	35.4	10.4	41.5	4	16

Source: PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,027,493 observations. The model regresses binary indicator on whether worker is employed in manufacturing sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Employment gains reflect the impact of increasing the share of formally trained workers under different scenarios (baseline, moderate, high) from 2024–25 to 2029–30.

3.4.3 Employment impacts in labour-intensive services sector

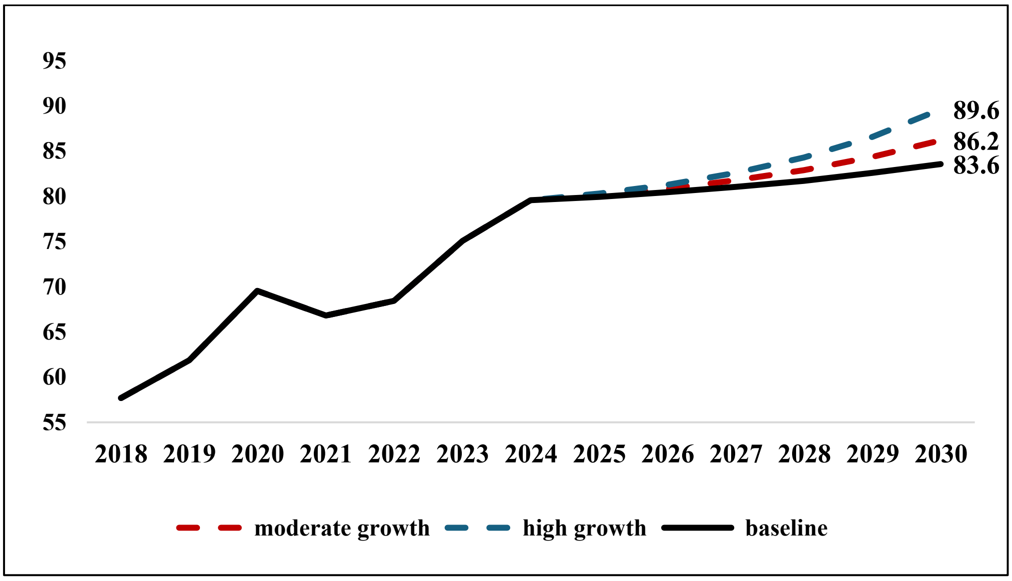
As of the base year 2024, the number of employed persons stands in labour intensive services stand at 79 million. **Figure 3.10** and **Table 3.2** shows the following results of the simulations:

- **Under the baseline scenario**, the share of formally trained workers is projected to increase from 4% in 2024 to 9% by 2030 (a rise of 5 pp points). The addition to the number of jobs in labour-intensive services is expected to be around 4 million, relative to the base year (column 4 of Table 3.2). This represents a 5.1% increase in employment compared to 2024 (column 5 of Table 3.2).

- **Under the moderate growth scenario**, the share of formally trained workers is projected to rise from 4% in 2024 to 13% by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 6.6 million, relative to the base year (column 4 of Table 3.2), representing an 8.4% increase (column 5 of Table 3.2).

- **Under the high growth scenario**, the share of formally trained workers is projected to rise from 4% in 2024 to 16% by 2030 (an increase of 12 pp points). The cumulative addition to jobs is projected to be around 10 million (column 4 of Table 3.2), corresponding to a 12.7% increase over the base year (column 5 of Table 3.2).

Figure 3.10: Employment in labour-intensive services (ages 15–59) under different scenarios (millions)



Source: PLFS (2017-18 to 2023-24); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,303,547 observations. The model regresses binary indicator on whether worker is employed in services sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Simulated employment gains under baseline, moderate, and high-growth scenarios in formal training reflect the potential impact of increasing the share of formally trained workers between 2024–25 and 2029–30; iv. Employment numbers are presented in millions.

Table 3.2: Cumulative addition to jobs in labour intensive services under different scenarios

Scenario	Employment in labour intensive services in 2024 (millions)	Employmen t in labour intensive services in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	79.6	83.6	4.1	5.1	4	9
Moderate Growth	79.6	86.2	6.6	8.4	4	13
High Growth	79.6	89.6	10.1	12.7	4	16

Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,303,547 observations. The model regresses binary indicator on whether worker is employed in services sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Employment gains reflect the impact of increasing the share of formally trained workers under different scenarios (baseline, moderate, high) from 2024–25 to 2029–30.

3.4.4 Employment impacts in aggregate labour intensive sectors

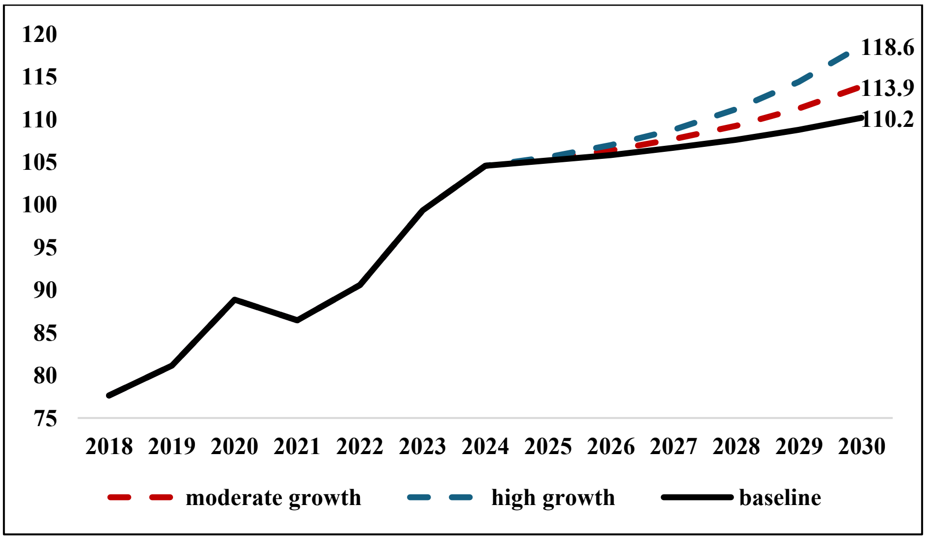
As of the base year 2024, the number of total employed persons in labour intensive manufacturing and services sectors stand at 104 million. **Figure 3.11** and **Table 3.3** shows the following results of the simulations:

- **Under the baseline scenario**, the share of formally trained workers is projected to increase from 4% in 2023-24 to 9% by 2030 (a rise of 5 pp points). The addition to the number of jobs in labour-intensive sectors is expected to be around 5.6 million relative to the base year (column 4 of Table 3.3). This represents a 5.4% increase in employment compared to 2024 (column 5 of Table 3.3).

- **Under the moderate growth scenario**, the share of formally trained workers is projected to increase from 4% in 2024 to 13% by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 9.2 million relative to the base year (column 4 of Table 3.3), representing around 8.9% increase (column 5 of Table 3.3).

- **Under the high growth scenario**, the share of formally trained workers is projected to increase from 4% in 2024 to 16% by 2030 (an increase of 12 pp points). The cumulative addition to jobs is projected to be around 14 million (column 4 of Table 3.3) corresponding to a 13.4% increase over the base year (column 5 of Table 3.3).

Figure 3.11: Employment in labour-intensive sectors (including both manufacturing and services (ages 15–59) under different scenarios (millions)



Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,434,391 observations. The model regresses binary indicator on whether worker is employed in manufacturing or services sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Simulated employment gains under baseline, moderate, and high-growth scenarios in formal training reflect the potential impact of increasing the share of formally trained workers between 2024–25 and 2029–30; iv. Employment numbers are in millions.

Table 3.3: Cumulative addition to jobs in labour intensive sector (including both manufacturing and services) under different scenarios

Scenario	Employment in labour intensive sector in 2024 (millions)	Employment in labour intensive sector in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Baseline	104.6	110.2	5.6	5.4	4	9
Moderate Growth	104.6	113.9	9.3	8.9	4	13
High Growth	104.6	118.6	14.0	13.4	4	16

Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. Projections are derived from simulations using a logit regression model estimated on PLFS data (2017–18 to 2023–24) for individuals aged 15–59 years, based on 1,434,391 observations. The model regresses binary indicator on whether worker is employed in manufacturing or services sector on a dummy variable that indicates whether worker is formally trained while controlling for education, gender, age, technical education, and location, with fixed effects for state and time; iii. Simulated employment gains under baseline, moderate, and high-growth scenarios in formal training reflect the potential impact of increasing the share of formally trained workers between 2024–25 and 2029–30.

This target set by Economic Survey accounts for both the expected increase in the workforce and a decline in the share of the workforce engaged in agriculture. Specifically, using this government target, we assess:

1. What share of formally trained workers would be required by 2030 to meet this employment target;
2. Whether the assumed increases of 0.5 SD and 1 SD in the share of formally trained workers (assumed under moderate and high growth scenarios, respectively) are conservative relative to what is actually required to meet the government target.

We make certain key assumptions:

- Untrained workers are assumed to grow at the average year-on-year (YoY) growth rate observed from 2018 to 2024 (excluding pandemic year of 2020-21).
- The employment target for 2030, based on the Economic Survey's goal of adding 7.8 million new non-farm jobs annually, is adjusted by the average share of employment in labour-intensive sectors (within manufacturing and services) to total non-farm employment of 39%.
- The target of job creation for labour intensive sectors is therefore, (78,00,000×0.39) 30,92,900 or 3.09 million per year. Over six years (2025 to 2030), this results in a cumulative employment requirement of 18.5 million new jobs.

We use Equation (3.3), which links employment gains to the increase in formally trained workforce to determine the share of trained workforce required to meet the economic survey target annually:

$$employment_{t+n} = employment_t + (\Delta_{t+n} \times (\mathrm{N}_{t+n} \times (Sharef trained_{t+n} - Sharef trained_t)))$$

The number of formally trained workers required in time t+n, denoted as x_{t+n} is obtained by rearranging Equation (3.3). We use the following expression:

$$x_{t+n} = \frac{1}{1-Sharef trained_t} * \left[\left(\frac{Emptarget_{t+n}-Employment_t}{\Delta_{t+n}}\right) + (Sharef trained_t * y_{t+n})\right] \quad (3.4)$$

Where:

- x_{t+n}: Formally trained workers required in year t+n
- y_{t+n}: Untrained workers in year t+n (based on average growth)
- Δ_{t+n}: marginal effect in year t+n
- $Sharef trained_t$ is share of formally trained worker in base year t
- $Emptarget_{t+n} - Employment_t$ is the difference between employment in base year and targeted employment as per the Economic Survey target in year t+n

The results (**Table 3.4**) suggest that, in order to meet the Economic Survey target—adjusted for the labour-intensive manufacturing and services sectors—the share of the formally trained workforce should increase to around 20% by 2030, compared to 5.4% in the baseline scenario. These estimates are slightly higher than those in the high-growth scenario, which projected the share of trained workers to reach 16% by 2030. In this sense, the high-growth scenario is conservative, as meeting the government's target requires an even greater increase in the share of formally trained workers. Therefore, the share of formally trained workers must grow rapidly if the Economic Survey target is to be met. If we do not adjust for the Economic Survey target and assume all non-farm jobs are created in labour intensive sectors within manufacturing and services, the required increase is much higher.

Table 3.4: Cumulative addition to jobs in labour intensive sector (including both manufacturing and services) if adjusted economic survey target is met

Scenario	Employment in labour intensive sectors in 2023–24 ('000s)	Employment in labour intensive sectors in 2029–30 ('000s)	Total Jobs created between 2029-30 and 2023-24 ('000s)	% increase in jobs created between 2029-30 and 2023-24	Share of formally trained workforce in 2023-24 (%)	Share of formally trained workforce in 2029-30 (%)
Baseline	104595	110191	5596	5.4	4	9
Economic Survey target	104595	123152	18557	17.7	4	20

Source: PLFS (2017-18 to 2023-24); Authors' calculations
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using KLEMS data; ii. The employment target is based on the Economic Survey's goal of creating 7.8 million non-farm jobs annually until 2029–30, adjusted for the average 39% share of labour-intensive sectors (within manufacturing and services) in total non-farm employment; iv. The required increase in the share of formally trained workers is estimated using logit regression results that link formal training to employment, in order to meet the Economic Survey target.

3.5. Summary

This section highlights a significant mismatch between the demand for skilled labour and the supply of formally trained workers in India. On the demand side, medium-skill jobs dominate employment growth, especially services, while manufacturing remains low-skill intensive. On the supply of skills, as of 2024, only 4% of workers have received formal training. Informal training is more common but does not necessarily translate into high-skill, regular employment. Formal vocational training, however, significantly increases the probability of securing high-skill, salaried jobs. Cross-country analysis shows India falling below the fitted trendline in the relationship between the share of trained workers and high-skill employment. This divergence highlights that quality—not just quantity—of training is a critical constraint.

4. Policy implications

Our projections of the number of jobs that can be created through output growth in labour intensive manufacturing and services sub-sectors between 2025 and 2030, using different growth scenarios, indicate that inter-sectoral linkages can have a multiplicative effect on employment in the aggregate economy, increasing employment by up to 200% relative to existing scenario. On the supply side, we show that increasing the share of skilled work force by 12 percentage points through investment in formal skilling could lead to more than a 13% increase in employment in the labour intensive sectors by 2030.

On average, labour-intensive manufacturing accounts for 44.1% of total manufacturing employment, while labour-intensive services account for 54.2% of total services employment. Combined, labour-intensive sectors constitute 51.3% of total employment in manufacturing and services. Our demand-side simulations indicate that we can significantly bridge the employment gap by increasing the size of the manufacturing and services sectors, particularly through a focus on labor intensive industries therein.

We underline the need for a multipronged approach to **increase production capacity** in labour intensive manufacturing and services sectors:

1. *Stimulate domestic demand through higher government expenditures and/or lower taxes:* The government has been taking initiatives on both these fronts, through high capex and the recent budgetary announcement on lower income tax rates – these measures need to be studied systematically to estimate impact on domestic demand. With the weakness in external demand, stimulating domestic consumption has become even more critical. Consistent policy focus on fiscally neutral measures that can effectively stimulate domestic demand is imperative to incentivize the private sector to invest in capacity expansion.

2. *Policy incentives to stimulate foreign and domestic investments in manufacturing and services sectors:* The central government has recently introduced the new version of the PLI scheme. However, the PLI scheme is primarily focused on expanding production of high value products with backward-linkages, which require high-skilled, specialised labour and are relatively less focused on low and middle-skilled labour intensive sectors. Specifically, over 50% of the PLI budget is allocated for large-scale electronics, IT hardware and drone manufacturing. However, the highest number of jobs under the scheme has been created in the food processing and pharmaceutical industry. Hence there is a mis-match between the weight of the budgetary allocation and the potential for employment creation.
   Case-in-point are textiles and footwear industries that have high labour intensity but lower exports than India's potential. Relatively lower U.S. tariffs than competitors such as Bangladesh and Vietnam, can boost India's textile and garment exports. In services sector, hotels and tourism have seen slow growth in foreign visitors and particularly poor recovery post pandemic. Here again, a policy driven focus on attracting both foreign tourists and domestic tourists is required. In addition, the opportunities in the labour intensive education sector remain untapped, given the demand stemming from the size of India's youth population, and the tightening of student immigration policies in the west.

3. *Loosen labour regulations:* Data show a persistent and steady decline in the labour intensity of production technology across sectors. This deepening of the capital intensity of the production process, particularly in and including labour intensive manufacturing and services industries, is likely to continue and fasten with the advent of AI. We cannot ignore the long-standing issue of loosening our labour regulations that artificially inflate the cost of labour and encourage the adoption of capital intensive technologies. Our analysis suggests that within the formal/registered manufacturing sector employment elasticities may have increased, in contrast to the observed decline in employment elasticity for the manufacturing sector as a whole. One possible

explanation for this is the increased hiring of contract labour to circumvent labour regulations. This underlines the need to allow more flexible hiring practices. The onus of adopting flexible labour policies, however, lies with the state governments.

4. *Credit expansion and ease of doing business*: Lower formal interest rates can increase credit take-up but only if businesses anticipate demand for their products. Our analysis of the ASUSE data on unincorporated non-agricultural establishments shows that access to credit can lead to significant increase in the GVA of an enterprise and thereby the size of the firm and its capacity to hire workers. At the same time, ease of registering and conducting business can significantly enhance value-added and thereby hiring.

On the supply side our simulations show that a formally skilled labour force is not only more likely to increase economic output, it is also more likely to be productively employed. Thus **productivity and quality of our workforce** has to be increased significantly to address the constraints in the supply of labour. The government has emphasized and increased investments in vocational skilling, with the 2025–26 doubling of the budget under MSDE allocation from Rs. 3,241 crore to Rs. 6,017 crore. The Skill India Mission supported by Pradhan Mantri Kaushal Vikas Yojana (PMKVY), Jan Shikshan Sansthan (JSS) and National Apprenticeship Promotion Scheme (NAPS) and other flagship schemes, mark important progress.

However, to meet the Economic Survey's goal of almost 8 million annual non-farm jobs, a rapid expansion of the formally trained workforce is essential. Additionally, the Future of Jobs Report 2025 highlights that 63% of India's workforce will need reskilling or upskilling by 2030 to remain competitive. Therefore, the focus must shift from merely expanding the skilling infrastructure to ensuring future readiness across the workforce, particularly with the advent of new technologies.

Our analysis shows that vocational training leads to a greater increase in employment in manufacturing compared to services, as most programs are tailored to meet specific industry needs. Incorporating soft skills, digital literacy and Information and Communication Technology (ICT) Skills into training programs can further enhance employability, particularly within these service sub-sectors. The poor outcomes of training in India stem from a combination of low formal training rates, misalignment of curricula with industry needs, lack of standardization, and the short-term nature of training programs. To address these issues, we suggest the following measures:

1. *Adoption of international best practices*: Several countries with successful vocational training systems (e.g., dual VET systems in Germany, Austria, and Singapore, the co-op system in Canada), combine classroom learning post high schooling with hands-on apprenticeships. This may require a systemic overhaul of our current education system that allows a student to choose between two streams of higher education – academic and vocational.

2. *Curriculum standards*: Ensure training curricula are co-developed with industry and updated every 2–3 years. This includes continuous adoption of new technologies and digital skills to enhance the relevance of skills to industry needs and keep pace with increased adoption of machinery. In a recently concluded RCT in Delhi and Bangalore, Afridi et al. (2025), show that the provision of digital skills training along with industry specific hard skills, significantly enhances women's entrepreneurship, raising their earnings from self-employment through increased usage of digital media to promote their businesses.

3. *Standardization and quality assurance*: There is a lack of trust in the quality of skill training provided by most institutions in the country. There is an urgent need to implement national quality benchmarks for training providers, including mandatory audits and continuous certification of trainers. Such a national skill accreditation agency should also ensure portability of workers' skill certification across employers and sectors.

   Our simulation results indicate under the "high growth" scenario, the gains from enhancing the marginal impact of training are more pronounced. The number of additional jobs rises to 14.8 million when both the share and the impact of training are increased, compared to 14.0 million when only the share is enhanced—resulting in 800,000 additional jobs. This corresponds to a 14.2% increase in employment, as opposed to 13.4 % under the scenario where only share of formally trained workers is increased. Thus, improving training quality, along with increasing the share of formally trained workers, can lead to higher employment gains.

4. *Short-term and on the job training*: Short-term training programs should not be seen as substitutes for formal vocational education, as they often are. Rather, they should be strategically used for upskilling existing workers within the industry. Investing in the human capital and skill upgradation of the workforce by employers is more likely when worker turnover is low and retention is high.

A concerted policy focus on the above measure will enhance the human capital of India's workforce while at the same time provide increasing avenues for gainful work.

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