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Pathways to Jobs: Rethinking Employment Strategies in India§

ABSTRACT We focus on the manufacturing and services sectors, particularly the more labor-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 labor 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 labor-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 the skilled work force by 12 percentage points through investment in formal skilling could lead to more than 13 percent increase in employment in the labor-intensive sectors by 2030. We conclude with policy prescriptions to boost aggregate demand and enhance workforce skilling.

Keywords: *Jobs, Economic Growth, Labor Intensity, Skilling*

JEL Classification: *J21, J23, J24*

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I. Introduction

The story of India's economic trajectory has been a hopeful one over the last four decades, buoyed by the liberalization 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 favorable expectations of strong economic performance in the coming future, in terms of both the size of its economy—a GDP of US$7 trillion by 2030, as per the *Economic Survey 2023-24* (Ministry of Finance 2024)—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 and 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, Ministry of Statistics and Programme Implementation 2019-2014). 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 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, which focuses on creating a future-ready workforce to complement and advance the agenda of 'Viksit Bharat'. As India moves up the production value chain, it needs to simultaneously invest in both the quantity and 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 labor.

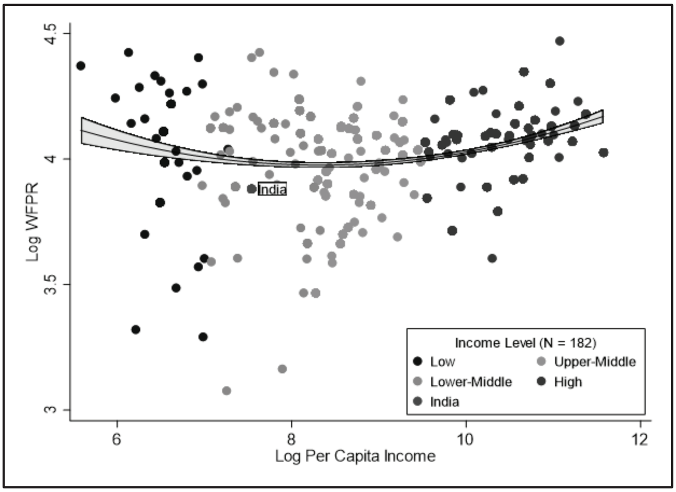
1.1. Labor Demand Constraints

There are two striking characteristics of India's labor force–first, the low, overall labor force participation rate of about 50 percent, 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).

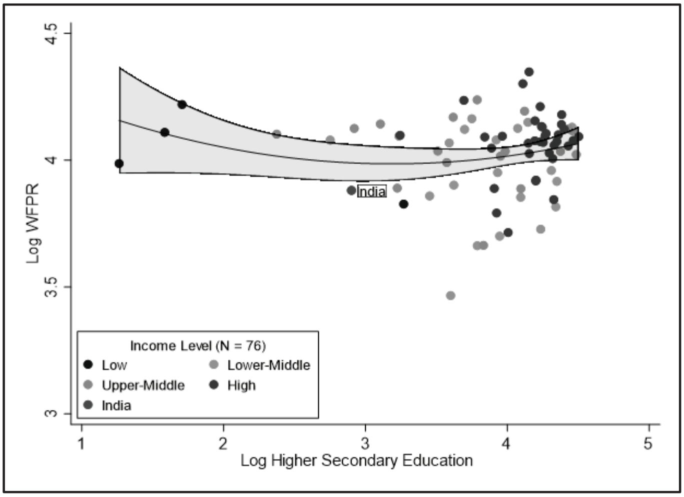
In addition, India with its large youth population, has been unable to capitalize on the demographic dividend. Youth workforce participation in India is below the international trend line (Figure 2).

FIGURE 1. Workforce Participation Rates (WFPR) by per Capita Income and Education

(a) WFPR versus Per Capita Income (2018)



(b) WFPR versus Higher Secondary Education (2018)

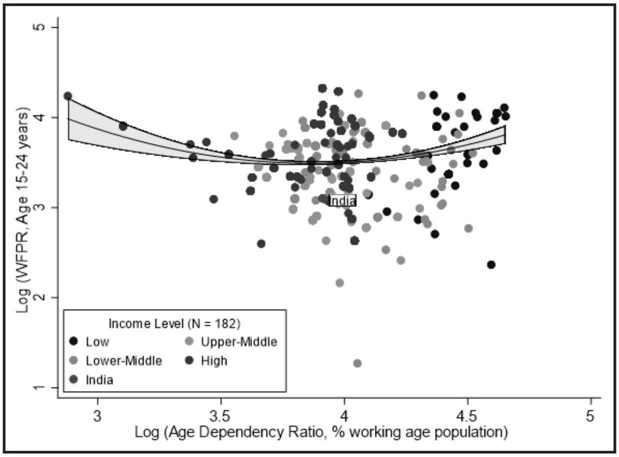


Source: Real GDP per capita (2015 USD) from World Bank database (2024); Data for employment and population from ILOSTAT (International Labour Organization 2023); Authors' calculations.

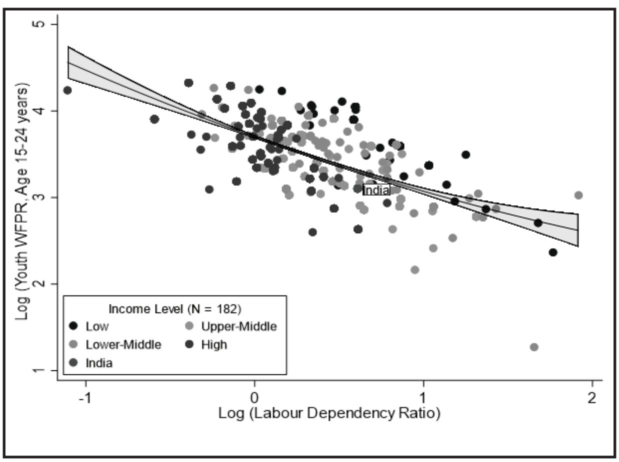
Note: i. WFPR (Workforce Participation Rate) = [(Total Employment/Total Population)*100] for age 15+; ii. Proportion of population with at least higher secondary education for ages 15+; iii. GDP per capita classifications follow the World Bank's 2017-18 thresholds; iv. 182 countries in Figure 1(a) and 76 countries in Figure 1(b); v. Both graphs use data from 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic; vi. 95% confidence interval bands.

FIGURE 2. Youth Workforce Participation Rate (WFPR) by Dependency Ratio

(a) Youth WFPR versus Age Dependency Ratio (2018)



(b) Youth WFPR versus Labor Dependency Ratio (2018)



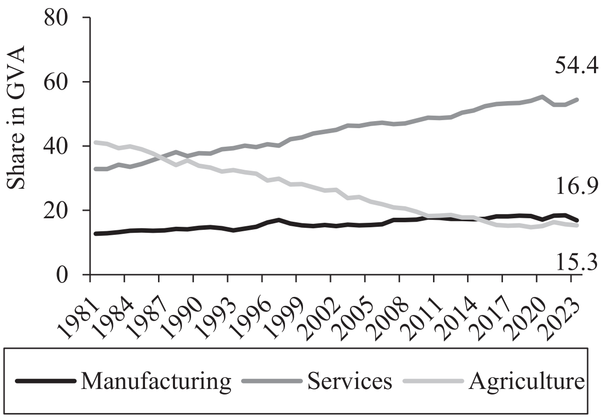
Source: Data on age from World Bank database (2024); Data for employment and population from ILOSTAT (International Labour Organization 2023); Authors' calculations.

Note: i. Youth WFPR = [(Employment/Population)*100] for ages 15-24; ii. Age Dependency Ratio measures the dependence of non-working age groups (young and elderly) on the working-age population; iii. Labor Dependency Ratio measures the number of economically inactive individuals (people not in the labor 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 2018, as it offers the most comprehensive dataset available prior to the onset of the COVID-19 pandemic; vii. 95% confidence interval bands.

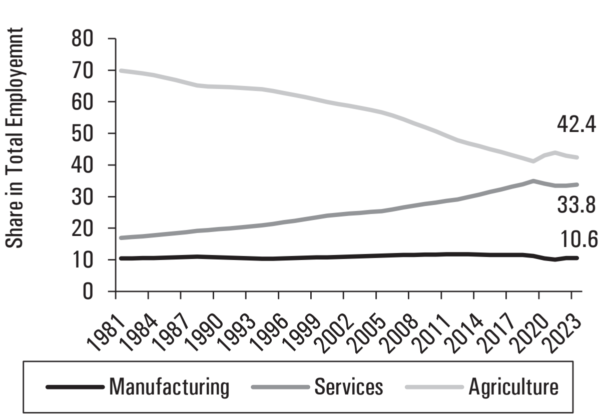
The second accompanying characteristic of India's labor force is the slow transformation, marked by an almost stagnant structure of labor force participation. Although the proportion of workforce employed in agriculture has declined, it still remains the largest at around 45 percent. This is despite a significant fall in agriculture's contribution to GDP (RBI 2024). The manufacturing sector's contribution to employment has been mostly stagnant with most of the labor shifting away from agriculture being absorbed by the services sector (Figure 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 3. Sectoral Shares in Total Gross Value Added (GVA) and Employment (India)

(a) Sectoral Share in Total GVA



(b) Sectoral Share in Total Employment

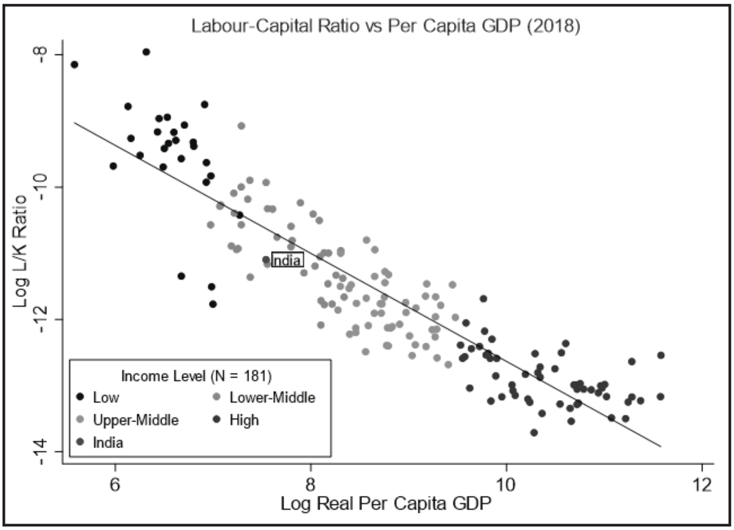


Source: RBI 2024; Authors' calculations.

Note: i. GVA is in 2011-12 constant prices; ii. The data span the period from 1981 to 2023, the latest year for which data are available.

These characteristics of India's labor force indicate constraints in productively absorbing its working-age population. We further highlight the demand-side constraints in labor absorption using the Penn World Table database, compiled by the Groningen Growth and Development Centre. We calculate the ratio of labor 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 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 labor use in India's production technology is relatively low.

FIGURE 4. Labor Intensity of Production by GDP Per Capita (2018)

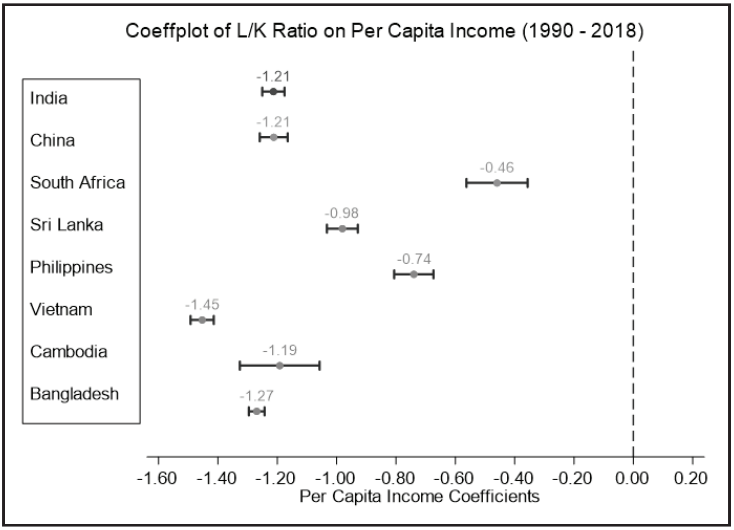


Source: Penn World Table (1990-2018), Groningen Growth and Development Centre (Feenstra et al. 2015); World Bank database (2024); Authors' calculations.

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 GDP per capita 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 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 labor 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 in Figure 5 shows the results of regressing the L/K ratio on per capita income to put into context India's rate of labor substitution as the GDP per capita grows.

FIGURE 5. Trends in Labor Intensity by GDP Per Capita (1990–2018) by Country



Source: Penn World Table (1990-2018), Groningen Growth and Development Centre (Feenstra et al. 2015); World Bank database (2024); 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 markings distinguish the World Bank Income Groups with the countries arranged in decreasing order of GDP per capita (2018) after India; v. 95% confidence interval bands.

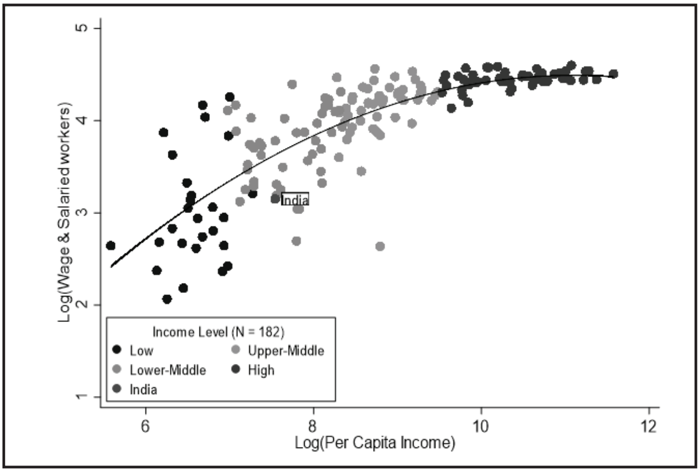
While there is a very visible trend of declining labor intensity of production across these countries, as indicated by the negative coefficients, India stands out as one of the countries experiencing a particularly sharp decline. As per the RBI KLEMS data, between 1981 and 2023, there has been a monotonic decline in labor employed relative to capital—the labor income share in value added has fallen by over 8 percent (RBI 2024).

The low levels of labor force transition, coupled with stagnant structural transformation, suggests constraints in expanding the demand for labor. The declining labor intensity of production further exacerbates the challenge of job creation, particularly as production technologies increasingly favor capital over labor (Grossman and Oberfield 2022). With the advent of Artificial Intelligence (AI) and automation, the relative cost of labor is likely to increase further. Capital deepening is occurring even in labor-intensive manufacturing and in services sub-sectors (Acemoglu and Guerrieri 2008). This is both surprising and concerning for a country like India, which is not only labor-abundant but is amidst a growing demographic dividend.

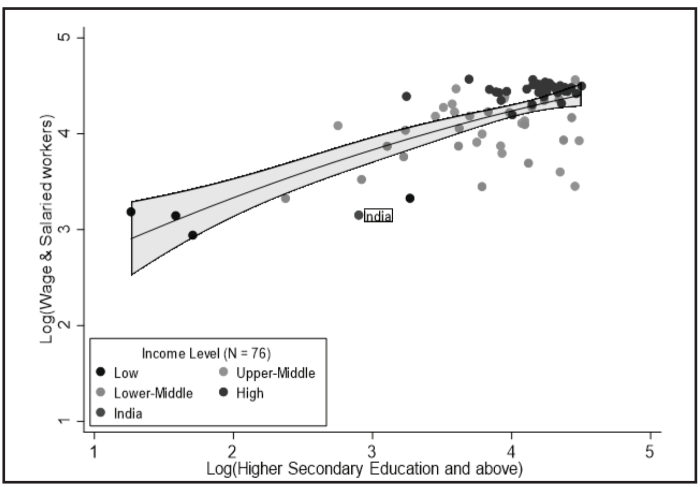
Not surprisingly, the data suggest that the paucity of "good" work opportunities impinges on the quality of work being done with significant underemployment across all occupations. Of those working, the share of self-employed in India is high, and rising (Afridi 2025). This stands contrary to the historical trend globally, where a rise in GDP per capita is associated with a fall in the share of self-employed and an increase in the share of salaried workers (Figure 6).

FIGURE 6. Proportion of Wage and Salaried Workers by GDP Per Capita and Education

(a) Wage and Salaried Workers versus Per Capita Income (2018)



(b) Wage and Salaried Workers versus Higher Secondary Education (2018)

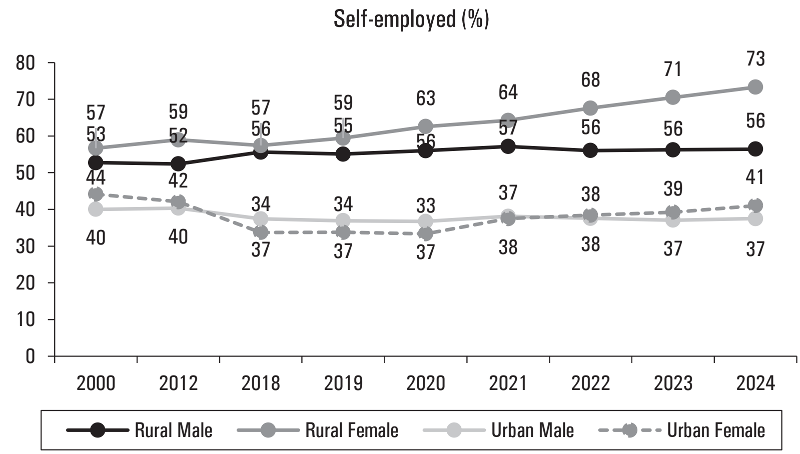


Source: Data for GDP per capita (constant USD, 2015), and for Wages and Salaried Workers is taken from the World Bank database (2024); data on population by different levels of education is taken from ILOSTAT (International Labour Organization 2023); Authors' calculations.

Note: i. Proportion of wage and salaried workers as a 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 6(a) consists of 182 countries and 6(b) of 76 countries; v. Both graphs use data from 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 percent of the workforce is categorized 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 7), along with a rise in the share employed in agriculture (post-pandemic). This suggests that self-employment is the fallback option for the working-age population.

FIGURE 7. Trends in Proportion of Self-employed (India)



Source: Periodic Labour Force Survey (PLFS Reports 2017-18 to 2023-24, Ministry of Statistics and Programme Implementation 2019-2024), National Sample Survey, 55th and 68th Rounds (NSS; 1999-2000, 2011-12). Authors' calculations.

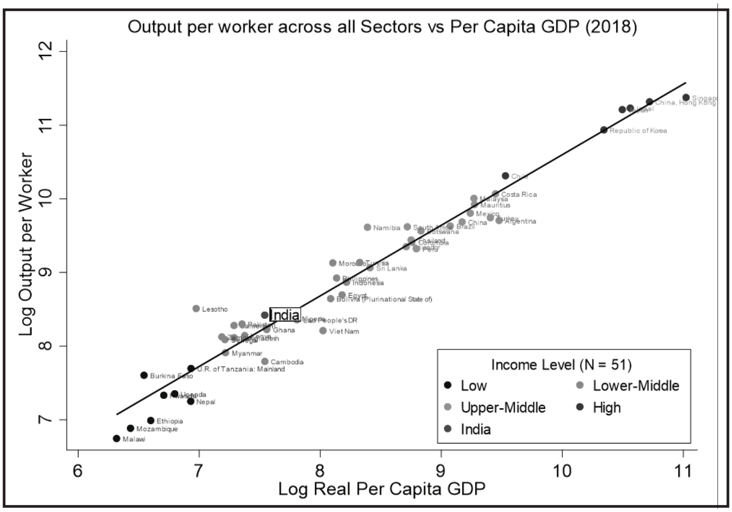
Note: i. Proportions are calculated as a percentage of total employment in each group; ii. The data span the period from 1999-2000 to 2023-24, the latest year for which data are available; iii. Sample size is of 16.9 crore in 1999-2000 and 26.8 crore in 2023-24 iv. The NSS rounds are included to exhibit a longer trend.

1.2. Labor Supply Constraints

While the previous section highlights the capacity constraints faced by the Indian economy in absorbing the labor force, we cannot ignore the presence of constrictions on the supply side of the labor 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 labor productivity and real per capita income and India's position relative to other countries. We, therefore, analyze the global patterns of labor 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 labor productivity (or output per worker) as the GVA (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 Figure 8.

FIGURE 8. Labor Productivity and Per Capita GDP



Source: Economic Transformation Database (ETD; 1990-2018), Groningen Growth and Development Centre (Kruse et al. 2022); World Bank database (2024); Authors' calculations.

Note: i. Output per worker is GVA (measured in constant 2015 USD) divided by the number of 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.

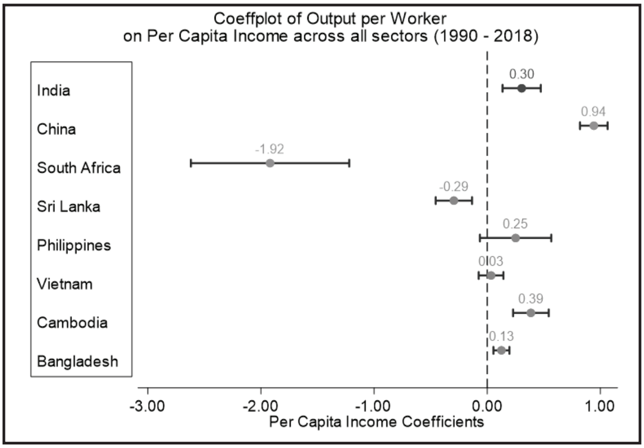
The scatter plot (Figure 8) indicates, expectedly, that the output per worker rises with increase in GDP per capita. India is slightly above the trend line. However, the analysis also shows that in order to reach the level of GDP per capita of high-income countries, India will need to increase its labor productivity significantly.

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

$$\text{Log(Labor Productivity)}_{it} = \beta_0 + \beta_1 \text{ Log(Per Capita GDP)}_{it} + \varepsilon_{it} \qquad (1)$$

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 9. Output Per Worker and GDP Per Capita (1990-2018)



Source: Economic Transformation Database (1990-2018), Groningen Growth and Development Centre (Kruse et al. 2022); World Bank database (2024); Authors' calculations.

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

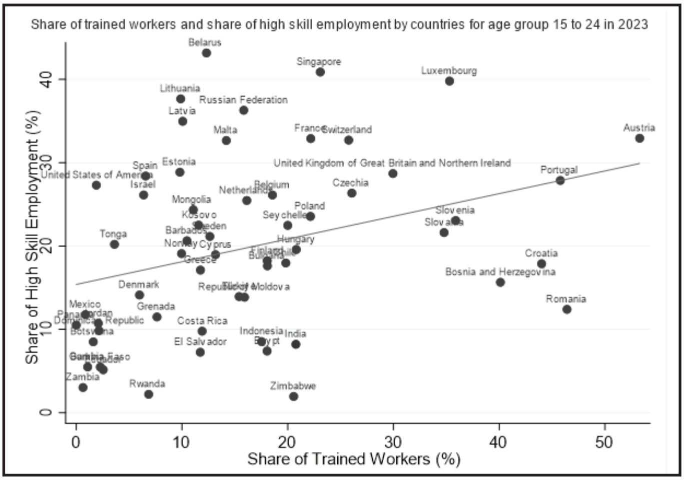
The coefficient plot in Figure 9 shows that while India's labor productivity has been growing along with growth in per capita income and keeping pace with similar lower middle-income economies, its labor productivity growth is slower than that of China. The relatively slow growth in labor productivity is accompanied by low share of high-skilled youth employment for the given proportion of skill-trained youth workers in India [Figure 10(a)]. The cross-country analysis suggests that India's quality of skill training may not be adequate enough to translate into high-skill employment.

More worryingly, for India's labor force as a whole, though the proportion of unskilled has been falling, the proportion with formal training has been more or less stagnant [Figure 10(b)]. It is not surprising, therefore, that the supply-side constraint on the quality of labor lowers the probability of being employed (as we discuss later in Section 3).

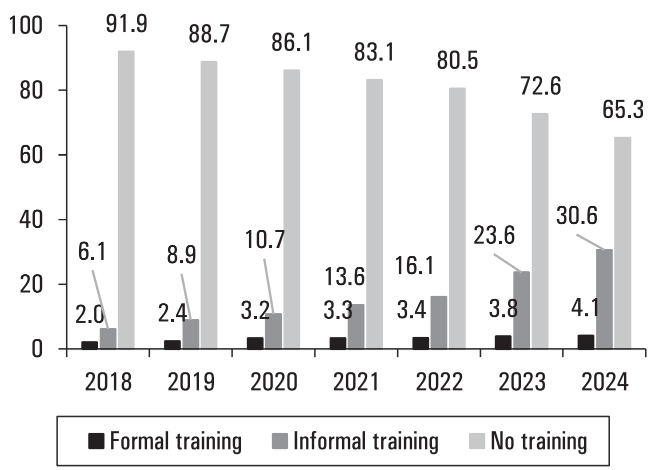
The analysis indicates that India needs to sharply increase the productivity of its labor force and invest in increasing the skill levels of its working age population to become "*viksit*". The low and poor-quality engagement of the working-age population, combined with increasing capital deepening across sectors, points to pressing challenges on both the supply and demand sides of the labor market. These dual constraints—limited supply of skilled labor 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.

FIGURE 10. High-Skill Employment and Trends in Worker Training

(a) Share of Trained Workers versus High-skill Employment



(b) Distribution of Workers by Training in India



Source: ILOSTAT, International Labour Organization (2023); PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; 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 10(a) is based on a sample of 58 countries.

In the following sections, we focus our analysis on the manufacturing and services sectors—particularly the more labor-intensive sub-sectors—as the share of agriculture in Gross Output (GO) 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 the 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 the services and manufacturing sectors, over the next five years, until 2030.

In Section 2, we propose measures to ease the demand side constraints and project the number of jobs that can be created through growth in the manufacturing and services sectors, particularly the labor-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 Labor Demand Constraints

Having examined and set into context the constraints on both the supply and demand sides of the labor market, as well as India's relative position in terms of labor 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 labor demand. Section 2.1 focuses on identifying the sectors and sub-sectors within manufacturing and services that have the greatest potential for employment generation by analyzing trends in labor 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 Labor Intensity of Production across Sectors (1981–2023)

To assess the potential for future job creation, we begin by analyzing trends in labor 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 (RBI 2024), we examine how labour has been utilized 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 labor-intensive over time.

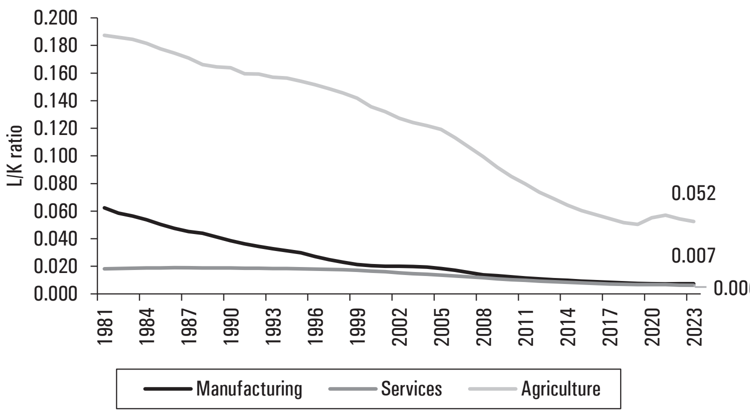
Ratio of Physical Labor to Physical Capital across Sectors

We define labor 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 labor compared to capital. A high L/K ratio implies that more labor is used per unit of capital. This is indicative of labor-intensive production. Since our objective is to identify sectors that absorb more units of labor, the L/K ratio is a more appropriate measure.[1] Measures such as labor 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 11. 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 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 the agricultural sector, followed by manufacturing.[2]

FIGURE 11. Labor to Capital (L/K) Ratio by Sector



Source: RBI 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 labor to capital (L/K) ratio represents labor intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data.

1. In the Indian context, the ASI data have 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.

2. We observe the same decline in labor 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 [Annual Survey of Industries (ASI) data, Ministry of Statistics and Programme Implementation 1981-2023].

In order to identify industries which are relatively more labor-intensive and hence likely to generate greater job opportunities, we classify sub-sectors within manufacturing and services as labor- or capital-intensive using the L/K ratio since it reflects the use of physical input quantities rather than input costs. It shows sub-sectors with median[3] or above labor intensity as relatively labor-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 labor-intensive include manufacturing sub-sectors such as, *Textile and Textile Products; Food Products and Beverages; Paper Products and Printing*; as well as the services sub-sectors such as *Trade, Hotels and Restaurants; Education; and Transport and Storage*. These industries consistently exhibit median or above-median labor-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 on some of these selected labor-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 labor-intensive based on its high use of labor 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 labor-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 labor when production scales up.

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3. The median labor to capital ratio is 0.006 for the manufacturing sector and 0.009 for the services sector. The sub-sectors with values equal to and above the median of the manufacturing or services sector are classified as labor-intensive.

4. Interestingly, using this classification, we find that the observed decline in labor intensity has been sharp in the more labor-intensive sub-sectors in both manufacturing and services, while the ratios have been relatively stable in the capital-intensive sub-sectors.

We calculate employment elasticity across sectors using the following 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 the broad sector to understand the general trends. We then focus specifically on the sub-sectors within manufacturing and services that were previously identified as labor-intensive based on the labor-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 Compound Annual Growth Rate (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 CAGR of employment to the CAGR of real value added:

$$\text{Employment elasticity} = \frac{CAGR\ of\ employment}{CAGR\ of\ value\ added} \qquad (2)$$

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.

$$LogL_t = \alpha + \beta LogY_t + e_t \qquad (3)$$

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 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]

TABLE 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*
	CAGR	0.329	0.335	0.215	0.220
Manufacturing	Log-log	0.357***	0.268***	0.188***	0.134*
		(0.023)	(0.029)	(0.028)	(0.064)
	CAGR	0.512	0.528	0.382	0.532
Services	Log-log	0.514***	0.513***	0.378***	0.523***
		(0.010)	(0.014)	(0.015)	(0.055)

Source: RBI 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. Labor is defined as the number of persons employed (in '000s). Value added is in constant prices (2011-12) (Rs crore). The standard errors are mentioned in parentheses. 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 labor-intensive (Table 2). We observe a consistent fall in employment elasticity across the labor-intensive manufacturing sub-sectors. However, employment elasticity has increased significantly in the education, health, and financial services sectors between 1981 and 2023. This indicates a significant potential of the labor-intensive services sub-sectors to create job opportunities.[6]

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

5. The difference between the 1980s and 2010s (1981 to 1990 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 2010s is not significant (p-value = 0.874), the elasticity values between the 1990s and 2000s are significantly different (p-value = 0.000)

6. Interestingly, employment elasticity in formal manufacturing has been increasing overall, as well as in the labor-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.

that arise through inter-sectoral linkages. As sectors expand, they not only create 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.

TABLE 2. Employment Elasticity Estimations Based on Log-Log Regressions for Labor-intensive Sub-sectors

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

Source: RBI 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. Labor is defined as the number of persons employed (in '000s). Value added is in constant prices (2011-12) (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 parentheses. The significance levels are denoted by ***, **, * for 1%, 5%, and 10% levels, respectively.

Every industry is connected to other economic sectors through backward linkages, which entail 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 (I-O) 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 labor-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 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, and Skills vertical of the National Council of Applied Economic Research (NCAER) in our analysis.

The National Statistical Office (NSO) releases Supply and Use Tables (SUT) (Ministry of Statistics and Programme Implementation 2019). 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 SUT 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 classification used in the India KLEMS database. We compute the Leontief Inverse matrix using the I-O table for 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

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).

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 ith 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

Labor output ratio: $E_i = \frac{L_i}{X_i}$

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

The total employment generated or number of jobs created by each sector was estimated by multiplying the sector's GO[8] for 2018-19 with the corresponding employment multiplier, derived from the input-output analysis. Considering that the SUT 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 that we classify as labor-intensive (Table 3).

8. We use GO data from the India KLEMS database (RBI 2024) to estimate total employment and the number of direct jobs. This enables us to incorporate information up to 2022–23.

TABLE 3. Employment Multiplier Estimations for Labor-intensive Sub-sectors

Sector	*Backward Linkage Employment Multiplier*	*No. of Persons per Rs. 1 Crore GVO* (at Current Prices)
Manufacturing		
Textile and textile products	0.047	47
Food products and beverages	0.088	88
Electrical and other equipment	0.030	30
Wood and wood products	0.089	89
Cement and other non-metallic minerals	0.026	26
Paper products, printing, and publishing	0.036	36
Gems, jewellery and 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 Tables 2018-19, Ministry of Statistics and Programme Implementation 2019; RBI 2024; Authors' calculations.

Note: i. We estimate employment multiplier for the sub-sectors using the I-O tables for 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 the 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 the following 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 labor-intensive sectors? In this simulation, we induce varying scenarios of growth in the GVA, 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 the following 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 forecast 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 forecast for 2025 to 2030 using this modified GVA growth rate.

To estimate projected growth rates of GVA, we assume that the 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) to arrive at the overall GVA values across the three sectors to estimate each GVA series' growth rate (Figure 12). Since Agriculture, Manufacturing, and Services together account for a significant share of total GVA (around 86.7 percent in 2023; Agriculture: 15.35 percent, Manufacturing: 16.92 percent and Services: 54.4 percent), 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 percent GDP growth rate, with a focus on the period up to 2030 (Table 4).

TABLE 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

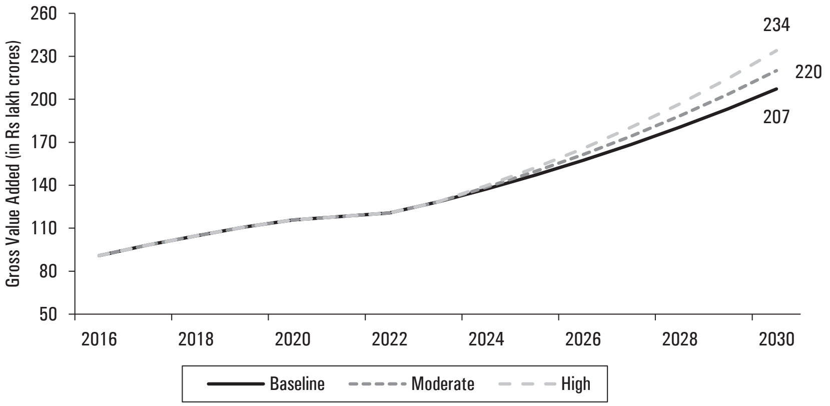
Source: Authors' calculations.
Note: GVA values are in constant 2011-12 prices (Rs. crores).

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

Our estimates indicate that if the manufacturing and services sectors grow at 8.2 percent and 9.0 percent, respectively, an overall GVA annual growth of 8 percent 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 a higher growth rate, that is, around 9 percent, if the manufacturing sector grows at 10.7 percent and the services sector grows at 9.6 percent. This is considered a 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 an 8 percent GVA growth could lead to significant employment generation across sectors, as shown in the following sections.[10]

FIGURE 12. Total GVA Projections



Source: RBI 2024; Authors' calculations.

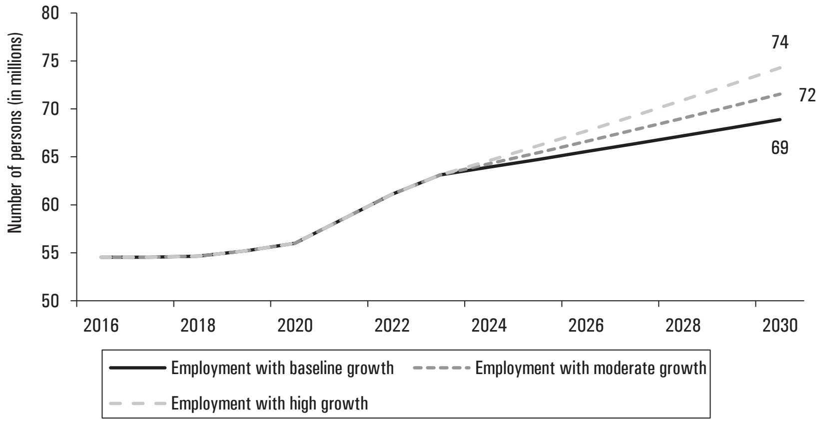
Note: i. GVA values are in constant 2011-12 prices. ii. The actual data used project GVA spans from 2011 to 2023; iii. Data for 2021 has been dropped to account for distortions caused by COVID.

A. Manufacturing Sector Simulations

The GVA (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 percent, on an average, during the period 2012 to 2023. The GVA of the manufacturing sector will grow at 8.2 percent in the moderate-growth scenario and at 10.7 percent in the high-growth scenario. Using the GVA from these three scenarios, the number of persons employed has been estimated using the CAGR method of employment elasticity.

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 percent and higher growth rate in the high-growth GVA scenario.

FIGURE 13. Projected Employment in the Manufacturing Sector



Source: RBI 2024; Authors' calculations.

Note: i. Labor is defined as the number of persons employed (in millions) and the GVA is in constant prices (2011-12) (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 span from 2012 to 2023.

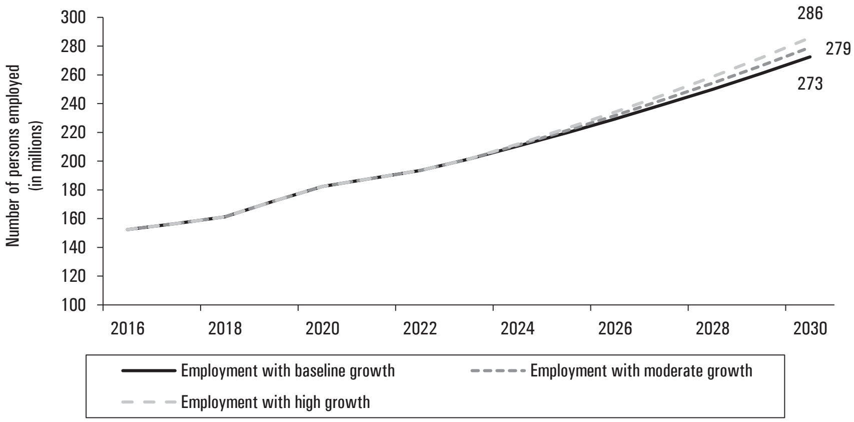
In the baseline growth scenario, the projected number of persons employed is 68.89 million. The projection for the number of persons employed in the moderate-growth scenario is 3.9 percent, higher than the baseline scenario, at 71.54 million persons. In the high-growth scenario, it is 7.8 percent higher than employment in the baseline scenario (Figure 13).

B. Services Sector Simulations

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

From Figure 14, we observe that in the services sector, 272.52 million persons are projected to be employed by 2030 with the baseline GVA growth. The projected number of persons employed increases by 2.4 percent to 279.13 million with moderate GVA growth. It increases by 4.9 percent to 285.88 million with high GVA growth.

FIGURE 14. Projected Employment in the Services Sector



Source: RBI 2024; Authors' calculations.

Note: i. Labor is defined as the number of persons employed (in millions) and the GVA is in constant prices (2011-12) (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 span from 2012 to 2023.

Overall, the projected employment under the moderate- and high-growth scenarios are as shown in Table 5.

TABLE 5. Projected Employment with Moderate and High GVA Growth

Year	*Manufacturing*		*Services*	
	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 crore).

Relative to the baseline scenario, employment in the overall manufacturing sector would increase by 3.9 percent under the moderate-growth scenario and at 7.8 percent in the high-growth scenario. In the services sector, on the other hand, the increase would be of 2.4 percent and 4.9 percent, 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 GO of the relatively more labor-intensive sub-sectors on job creation through inter-sectoral linkages.

2.4.2. Changing GO for Given (Backward) Multiplier for Sub-Sectors

In this simulation, we induce changes to the GO, keeping the (backward) employment multiplier for 2018-19 constant, that is, 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:* The 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 forecast using this modified GO growth rate.
3. *High-growth Scenario:* The 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 forecast 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 labor-intensive sub-sector.[11]

A. Manufacturing Labor-intensive Sub-sectors

The GO for the textiles industry, as of 2023, is Rs 1,534,041 crore. The GO grew at 11.1 percent, on an average, from 2012 to 2023. This growth rate has been considered to construct the baseline scenario. The GO is expected to grow at 18.5 percent in the moderate-growth scenario, and at 25.9 percent in the high-growth scenario.

In the baseline scenario, the GO grows at the rate of the average growth rate for the period from 2012 to 2023. As a result, the cumulative number of jobs created through an increased output of the textile, leather, and footwear industry, is projected at 150,704,000 by the year 2030. The projected numbers of aggregate economy-wide jobs created in the moderate- and high-growth scenarios increase by 57 percent and 140 percent, respectively, relative to the baseline growth scenario (Figure 15).

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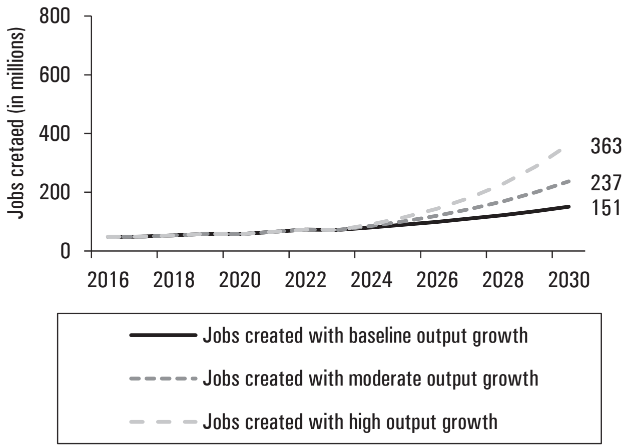
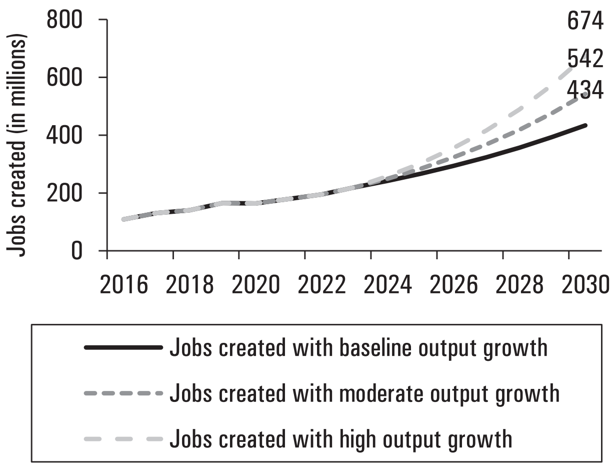
11. The year 2020-21 has been dropped when estimating the average growth rate for the period under consideration.

FIGURE 15. Projected Job Creation (Manufacturing Multiplier)

(a) Textiles and Textile Products



(b) Food Products and Beverages



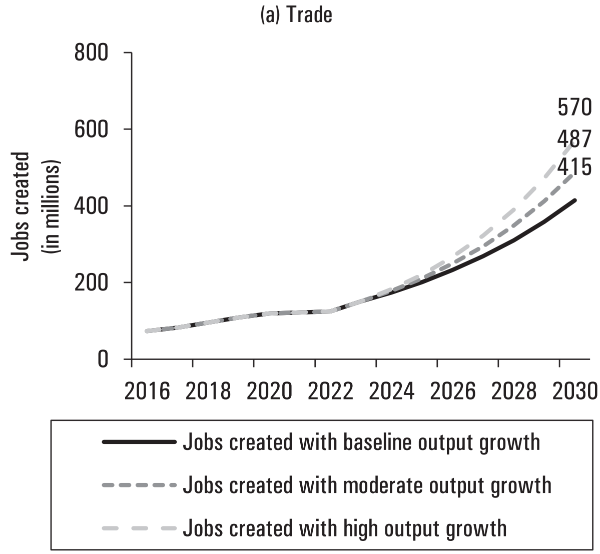
Source: Supply-Use Table 2018-19, Ministry of Statistics and Programme Implementation 2019; RBI 2024; Authors' calculations.

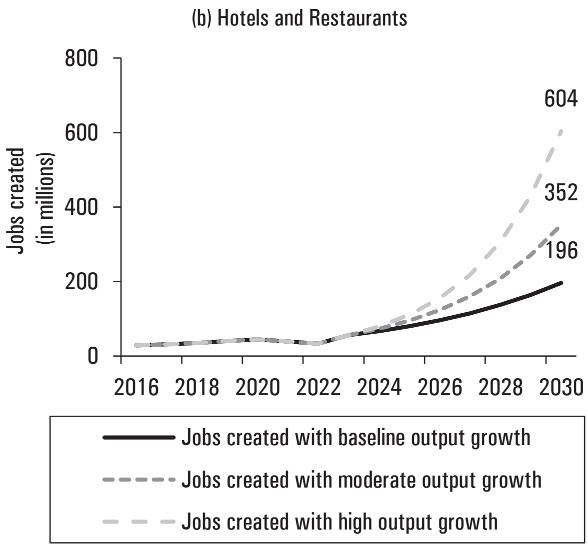
Note: i. The period of analysis is from 2012 to 2023; ii. The GO is in current prices; iii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic.

B. Services Labor-intensive Sub-sectors

Similarly, taking into account the employment multiplier in the two most labor-intensive sub-sectors (that is, Trade, and Hotels and Restaurants) in services, we estimate that the total number of aggregate economy-wide jobs created by 2030 would increase by 18–79 percent with a moderate increase in the GO of these services sub-sectors and 37–200 percent in the high-growth scenario (Figure 16).

FIGURE 16. Projected Job Creation (Services Multiplier)





Source: Supply-Use Tables 2018-19, Ministry of Statistics and Programme Implementation 2019; RBI 2024; Authors' calculations.

Note: i. The period of analysis is from 2012 to 2023; ii. The GO is in current prices; iii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic.

2.5. Summary

The simulation exercises indicate that increasing investment in the labor-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 labor-intensive sub-sectors. We summarize the policy implications later in Section 4.

3. Unleashing Supply of Quality Labor

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

3.1. Demand for Skills

3.1.1. Skill Distribution in the Aggregate Economy

As shown in Figure 17, 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 percent in 2018 to nearly 50 percent 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 (y-o-y) 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.

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 percent of the total manufacturing employment in 2024. In contrast, the agriculture and services sectors are dominated by medium-skill employment, comprising 82 percent and 43 percent of their respective workforces in 2024, respectively.

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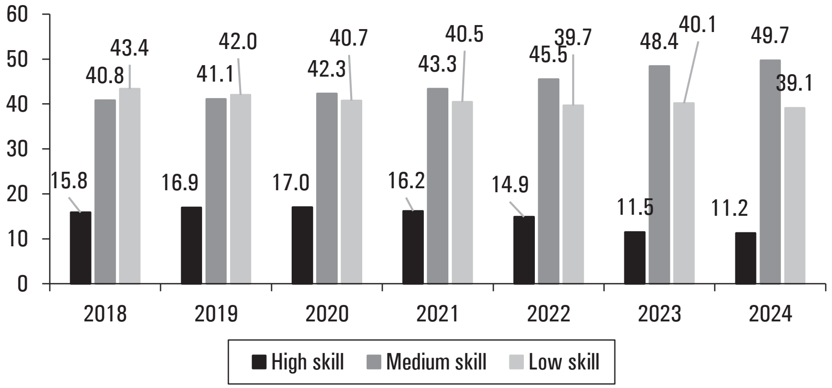
12. Skill categorization is based on the first-digit classification of National Classification of Occupations (NCO) codes. The following classifications have been used: High-skilled: Legislators, Senior Officials, and Managers; Professionals; and Associate Professionals; Medium-skilled: Clerks; Service Workers and Shop and 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.

FIGURE 17. Employment Distribution and Employment Trends by Skills for Workers Aged 15-59 Years (%)

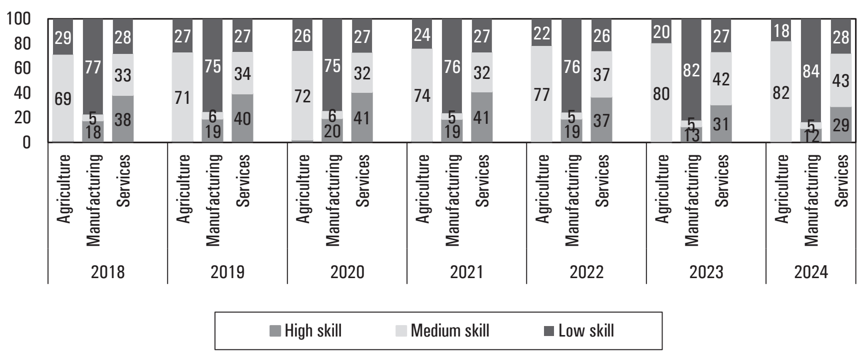


Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The manufacturing sector includes 2-digit industry codes from 10 to 33 and the services sector includes 2-digit industry codes from 45 to 99; ii. Skill categorization is based on NCO (1-digit level). Weighted sample size varied from 341 million in 2017-18 to 475 million in 2023-24.

High-skill employment is primarily concentrated in the services sector, where it accounted for 29 percent of employment in 2024 (Figure 18).

FIGURE 18. Employment Distribution by Skills (%)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The agriculture sector includes 2-digit industry codes from 01 to 03; The manufacturing sector includes 2-digit industry codes from 10 to 33 and the 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 varied from 143.98 million in 2017-18 to 207.41 million in 2023-24; in manufacturing, it varied 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.

The share of medium-skill employment has increased significantly in agriculture—from 69 percent in 2017–18 to 82 percent in 2023–24—and in services, from 33 percent to 43 percent, 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 percent to 12 percent in manufacturing, and from 38 percent to 29 percent in services, between 2018 and 2024. The share of low-skill employment has decreased in agriculture (from 29 percent to 18 percent), remained relatively stable in services (around 28 percent), but increased in manufacturing (from 77 percent to 84 percent).

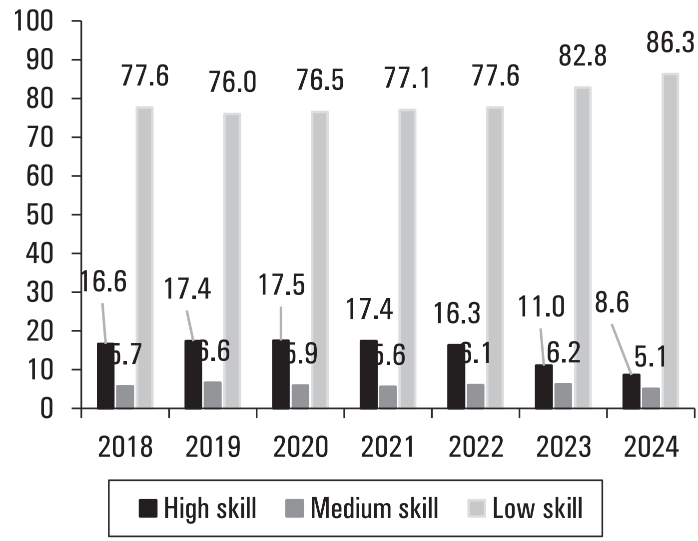
The y-o-y employment growth in the agriculture and services sectors has been highest for medium-skill jobs (except in 2023-24 where low-skill employment showed the highest growth). Within manufacturing, low-skill employment has shown the highest growth for the last two years. Although high-skill employment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

3.1.3. Skill Distribution within the Labor-intensive Sectors

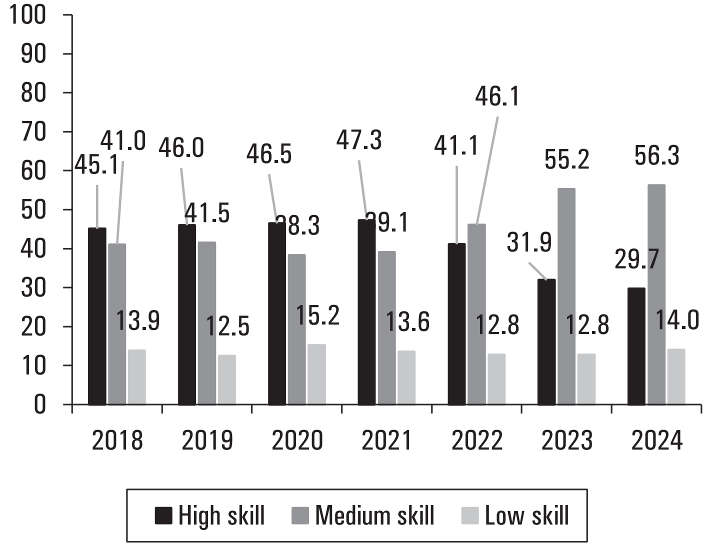
As per Figure 19, the labor-intensive manufacturing sector is dominated by low-skill employment. However, the labor-intensive services sector is dominated by medium-skilled workers.

FIGURE 19. Employment Distribution by Skills within Labor-intensive Sectors for Workers Aged 15-59 Years (%)

(a) Labor-intensive Manufacturing



(b) Labor-intensive Services



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

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

The y-o-y employment growth in labor-intensive services is mostly the highest for medium-skilled workers. However, in 2024, growth was higher for low-skill employment within labor-intensive services. In labor-intensive manufacturing, low-skilled workers recorded the highest employment growth.

3.2. Supply of Skills

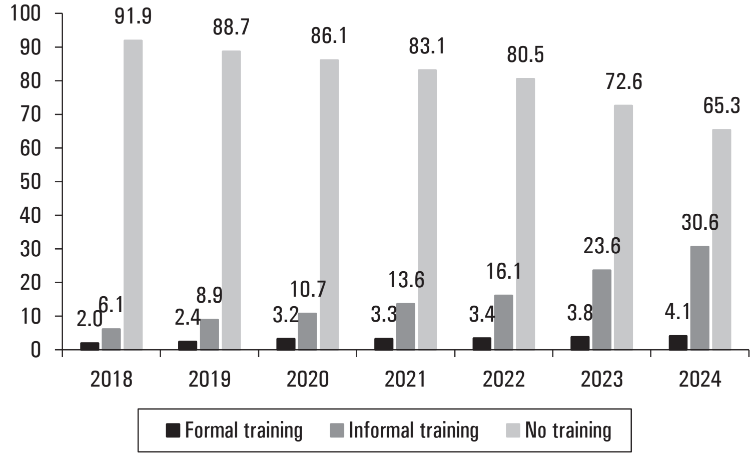
3.2.1. Supply of Skills in the Aggregate Economy

There has been a decline in the share of untrained workers over time. In 2018, 92 percent of the workers had no training, which fell to 65 percent by 2024. However, the majority of workers remain untrained. As of 2024, only 4 percent of the workers had received formal training. Moreover, the y-o-y growth in the number of formally trained workers is lower than the growth in the number of informally trained workers (Figure 20).

3.2.2. Sectoral Supply of Skills

Figure 21 shows that the agriculture and services sectors are dominated by workers who have not received any training, followed by those who have received informal training. The manufacturing sector is dominated by workers who have received informal training. A negligible proportion of workers have formal training within the agriculture sector. The share of workers who have received formal training is highest among the services sector, at 8.7 percent.

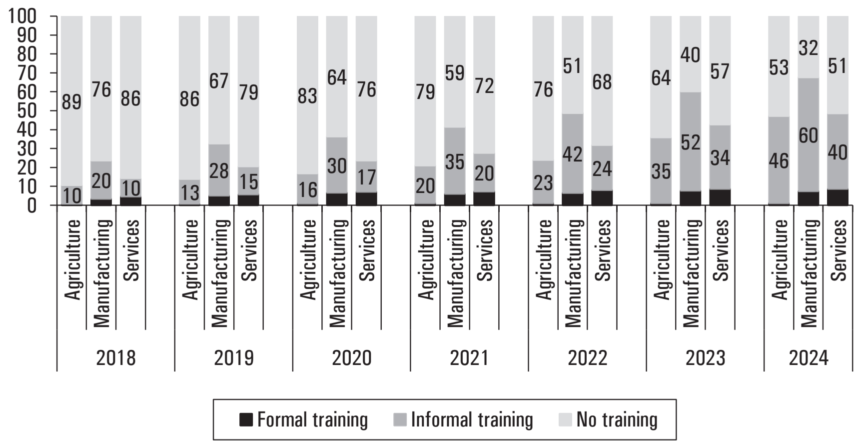
FIGURE 20. Distribution of Workers Aged 15-59 Years by Training (%)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. Informal training includes hereditary, self-learning, learning on the job, and other types of training; ii. Weighted sample size varied from 688 million in 2017-18 to 765 million in 2023-24.

FIGURE 21. Workforce Distribution by Training within Sectors (%)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

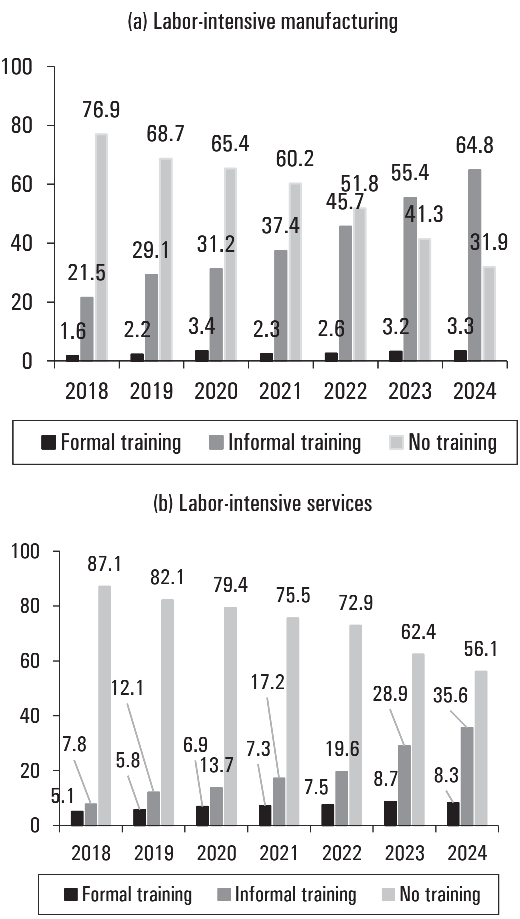
Note: i. The agriculture sector includes 2-digit industry codes from 01 to 03; the manufacturing sector includes 2-digit industry codes from 10 to 33; and the services sector includes 2-digit industry codes from 45 to 99; ii. Informal training includes hereditary, self-learning, learning on the job, and other types of training; iii. Weighted sample size within agriculture varied from 143 million in 2017-18 to 207 million in 2023-24; in manufacturing from 43 million in 2017-18 to 57 million in 2023-24; and within services, from 109 million in 2017-18 to 147 million in 2023-24.

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

3.2.3. Supply of Skills within the Labor-intensive Sectors

The labor-intensive services sector is dominated by untrained workers. Labor-intensive manufacturing is dominated by informally trained workers (Figure 22).

FIGURE 22. Workforce Distribution by Training within Labor-intensive Sectors for Age Group 15-59 Years (%)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations

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

The y-o-y growth in the formally trained workforce is lower than that of the informally trained workforce, within both labor-intensive manufacturing and services 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 the maximum 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-skill 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 that 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-skill 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 PLFS data for 2024. The analysis is restricted to young workers aged 15-29 years, who represent the segment of the population transitioning into the workforce.

$$Log\left[\frac{P(employed_{it})}{1-P(employed_{it})}\right] = \beta_o+\beta_1 training_{it}+\beta_2 gender_i+\beta_3 age_{it}+ \beta_4 geduc_{it}+\beta_5 technedu_{it}+ \beta_6 location_{it}+\gamma_s+\gamma_t+\varepsilon_s \quad (4)$$

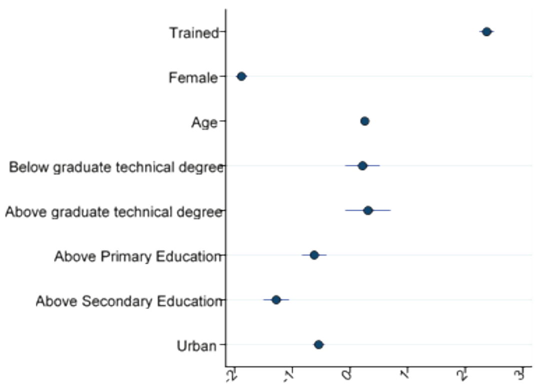
$employed_{it}$ is the binary variable that takes value 1 if the worker i is employed at time t and 0 if he is unemployed. Specifically, in regression 1, it takes value 1 if the worker is employed in any job, in regression 2, it takes value 1 if the worker is engaged in a regular job, and in regression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

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

gender$_{it}$ is a variable that takes value 1 for a male worker and 2 for a female worker;
age$_{it}$ is a 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 23 shows the log-odds of being employed in any job, as estimated by logistic model Equation 4.

FIGURE 23. Log (Odds) of Being Employed in Any Job in 2024 for Workers Aged 15-29 Years

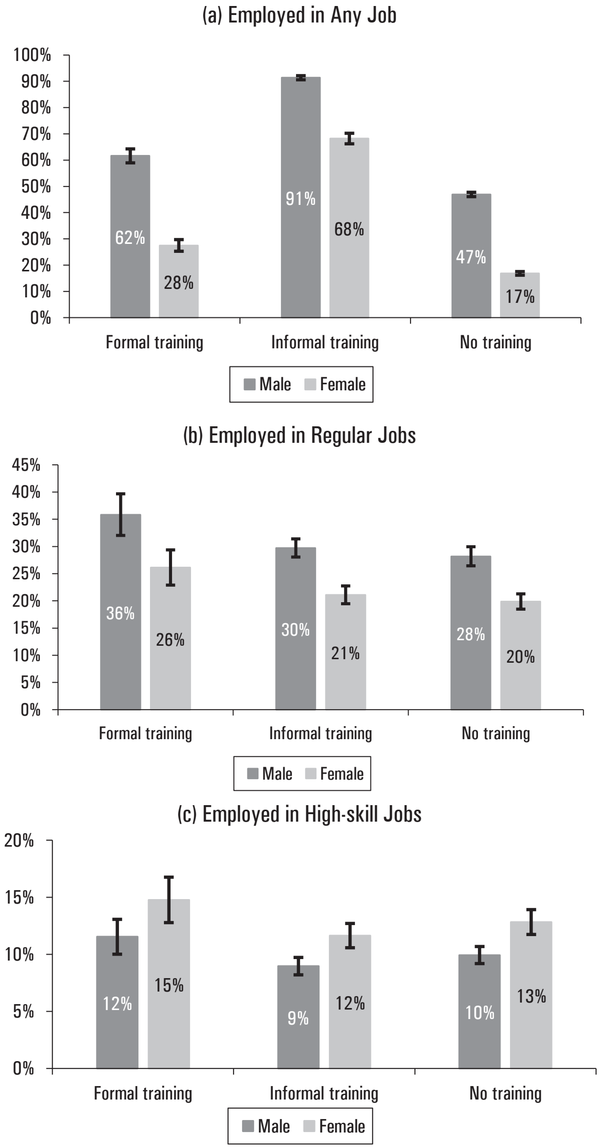


Source: PLFS (2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.
Note: i. Log (Odds) is based on a logit regression based on PLFS data (2017–18 to 2023–24) that regress whether the worker is employed in any job and whether the worker is trained, years of general education, types of technical education received by the worker, age, location (rural/urban) and state-fixed effects, for workers aged 15- 29 years; ii. Coefficients are plotted with 99% confidence bands; iii. The weighted number of observations for the regression is 109,048.

Figure 23 shows that having vocational training and technical education is positively associated with the 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 24 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 24. Predicted Probability of Being Employed Based on Training Level of Workers Aged 15-29 Years (%)



Source: PLFS (2023-24), Ministry of Statistics and Programme Implementation 2019-2024; 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 labor force. Regular job employment is coded as 1 if employed in regular jobs and 0 if casual or self-employed. High-skill employment is coded as 1 if employed in high-skill jobs and 0 if in low or medium-skill 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-skill 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 as 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, in 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 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 15-59 years over the period 2017–18 to 2023–24. The specification is as follows:

$$Log\left[\frac{P(employed_{it})}{1-P(employed_{it})}\right]=\beta_0+\beta_1 formaltraining_{it}+\beta_2\, gender_i+\beta_3 age_{it}+\beta_4\, geduc_{it}+\beta_5 technedu_{it}+\beta_6 location_{it}+\gamma_s+\delta_t+\varepsilon_{it} \qquad (5)$$

where:

For projecting employment for labor-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 labor-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 the labor-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.

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

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

ageit is a 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;
δ_t are the time fixed effects;
ε_{it} is the error term.

Using Regression Equation (5), the simulation estimates how increases in the share of formally trained workers affect employment in the labor-intensive manufacturing sector, labor-intensive services sector, and the labor-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 services 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 the logit model.

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

$$employment_{t+n}=employment_t+(\Delta_{t+n}\times(N_{t+n}\times(Sharef trained_{t+n}-Sharef trained_t))) \quad (6)$$

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.
- $Sharef trained_{t+n}$-$Sharef trained_t$ 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, following are the simulation scenarios:

1. *Baseline*: It is assumed that the y-o-y growth in the number of formally trained workers and the number of informally trained workers is equal to

their respective average y-o-y growth rates observed between 2018 and 2024 (excluding 2021). These growth rates are applied uniformly for each projection year from 2025 to 2030.

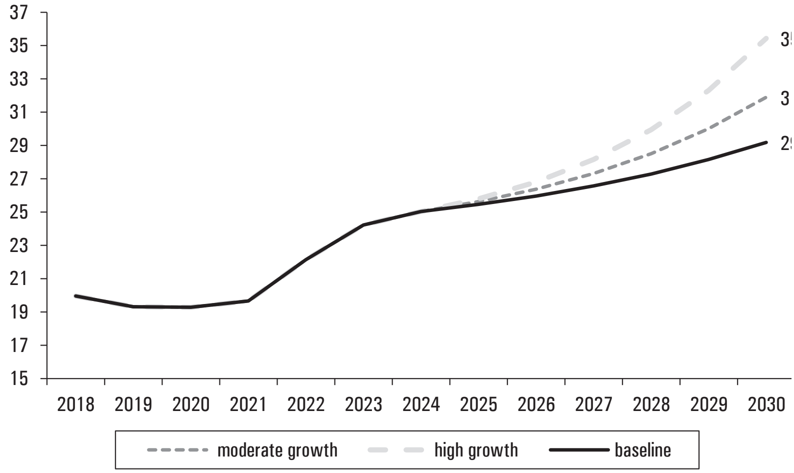
2. *Moderate Increase in Number of Formally Trained Workers*: It is assumed that the y-o-y growth in the number of formally trained workers is 0.5 SD above the average y-o-y growth observed between 2018 and 2024 (excluding 2020–21). The number of informally trained workers continues to grow at the average y-o-y growth rates observed between 2018 and 2024 (excluding 2021). These rates are applied uniformly for each projection year 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 above the average y-o-y growth observed between 2018 and 2024 (excluding 2021). The number of informally trained workers continues to grow at the average Y-o-Y growth rates observed between 2018 and 2024 (excluding 2021). These growth rates are applied uniformly for each projection year from 2025 to 2030.

3.4.2. Employment Impacts in the Labor-intensive Manufacturing Sector

As of the base year 2024, the number of employed persons in labor-intensive manufacturing stands at 25 million. Figure 25 and Table 6 show the following results of the simulations:

- *Under the baseline scenario,* the share of formally trained workers is projected to increase from 4 percent to 9 percent (a rise of 5 percentage points) by 2030. The addition to the number of jobs in labor-intensive manufacturing is expected to be around 4.1 million, relative to the base year (Column 4 of Table 6). This represents a 16.6 percent increase in employment as compared to 2024, within labor-intensive manufacturing (Column 5 of Table 6).
- *Under the moderate-growth scenario,* the share of formally trained workers is projected to rise from 4 percent in 2024 to 13 percent by 2030 (an increase of 9 percentage points). The expected addition to jobs is approximately 6.8 million, relative to the base year (Column 4 of Table 6) representing a 27.4 percent increase, within labor-intensive manufacturing (Column 5 of Table 6).
- *Under the high-growth scenario,* the share of formally trained workers is projected to rise from 4 percent in 2024 to 16 percent by 2030 (a rise of 12 percentage points). The cumulative addition to jobs is projected to be around 10.3 million (Column 4 of Table 6), representing a 41.5 percent increase over the base year (Column 5 of Table 6).

FIGURE 25. Employment in Labor-intensive Manufacturing (ages 15–59 Years) under Different Scenarios (Millions)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-to-capital (L/K) ratio and a significant contribution to Gross Value of Output (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-growth, 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.

3.4.3. Employment Impacts in the Labor-intensive Services Sector

As of base year 2024, the number of employed persons in labor-intensive services stands at 79 million. Figure 26 and Table 7 show the following results of the simulations:

- *Under the baseline scenario,* the share of formally trained workers is projected to increase from 4 percent in 2024 to 9 percent by 2030 (a rise of 5 percentage points). The addition to the number of jobs in labor-intensive services is expected to be around 4 million, relative to the base year (Column 4 of Table 7). This represents a 5.1 percent increase in employment as compared to 2024 (Column 5 of Table 7).
- *Under the moderate-growth scenario*, the share of formally trained workers is projected to rise from 4 percent in 2024 to 13 percent by 2030 (an increase of 9 percentage points). The expected addition to jobs is

TABLE 6. Cumulative Addition to Jobs in Labor-intensive Manufacturing under Different Scenarios

Scenario	*Employment in Labor-intensive Manufacturing in 2024 (Millions)*	*Employment in Labor-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

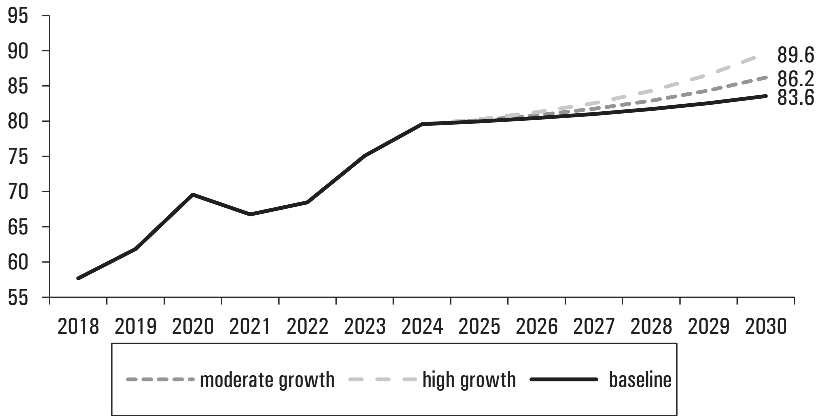
Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 the worker is employed in the manufacturing sector on a dummy variable that indicates whether the 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-growth, high-growth) from 2024–25 to 2029–30.

approximately 6.6 million, relative to the base year (Column 4 of Table 7), representing an 8.4 percent increase (Column 5 of Table 7).

- *Under the high-growth scenario,* the share of formally trained workers is projected to rise from 4 percent in 2024 to 16 percent by 2030 (an increase of 12 percentage points). The cumulative addition to jobs is projected to be around 10 million (Column 4 of Table 7), corresponding to a 12.7 percent increase over the base year (Column 5 of Table 7).

FIGURE 26. Employment in Labor-intensive Services (Aged 15–59 Years) under Different Scenarios (Millions)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 a binary indicator on whether the worker is employed in the services sector on a dummy variable that indicates whether the 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 the baseline, moderate-growth, 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.

3.4.4. Employment Impacts in the Aggregate Labor-intensive Sectors

As of base year 2024, the number of total employed persons in the labor-intensive manufacturing and services sectors stands at 104 million. Figure 27 and Table 8 show the following results of the simulations:

- *Under the baseline scenario,* the share of formally trained workers is projected to increase from 4 percent in 2023-24 to 9 percent by 2030 (a rise of 5 percentage points). The addition to the number of jobs in the

TABLE 7. Cumulative Addition to Jobs in the Labor-intensive Services under Different Scenarios

Scenario	*Employment in Labor-intensive Services in 2024 (Millions)*	*Employment in Labor-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

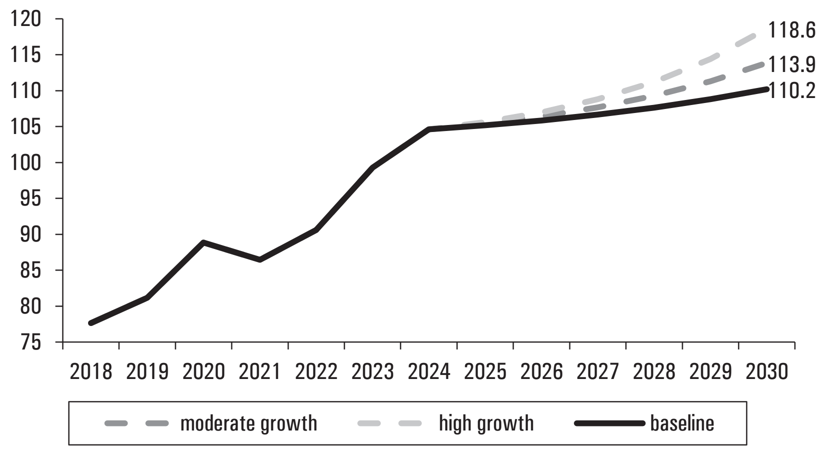
Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 a binary indicator on whether the worker is employed in the services sector on a dummy variable that indicates whether the 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-growth, high-growth) from 2024–25 to 2029–30.

labor-intensive sectors is expected to be around 5.6 million, relative to the base year (Column 4 of Table 8). This represents a 5.4 percent increase in employment as compared to 2024 (Column 5 of Table 8).

- *Under the moderate-growth scenario,* the share of formally trained workers is projected to increase from 4 percent in 2024 to 13 percent by 2030 (an increase of 9 percentage points). The expected addition to jobs is approximately 9.2 million, relative to the base year (Column 4 of Table 8), representing an around 8.9 percent increase (Column 5 of Table 8).
- *Under the high-growth scenario,* the share of formally trained workers is projected to increase from 4 percent in 2024 to 16 percent by 2030 (an increase of 12 percentage points). The cumulative addition to jobs is projected to be around 14 million (Column 4 of Table 8) corresponding to a 13.4 percent increase over the base year (Column 5 of Table 8).

FIGURE 27. Employment in Labor-intensive Sectors, including both Manufacturing and Services (Aged 15–59 Years) under Different Scenarios (Millions)



Source: PLFS (2017-18 to 2023-24), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 a binary indicator on whether the worker is employed in the manufacturing or services sector on a dummy variable that indicates whether the 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-growth, 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; v. Employment numbers are in millions.

TABLE 8. Cumulative Addition to Jobs in the Labor-intensive Sectors (Including Both Manufacturing and Services) under Different Scenarios

Scenario	*Employment in Labor-intensive Sector in 2024 (Millions)*	*Employment in Labor-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), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 a binary indicator on whether the worker is employed in the manufacturing or services sector on a dummy variable that indicates whether the 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-growth, 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.

3.4.5. Employment Impacts in the Labor-intensive Sectors for the Given Government Target

Do the growth scenarios achieve the government's skilling target? The purpose of this simulation is to estimate the required share of formally trained workers needed to meet the *Economic Survey 2024* target of creating 7.8 million new non-farm jobs annually until 2030. This target set by the *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 the following questions:

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

We make certain key assumptions, as follows:

- Untrained workers are assumed to grow at the average y-o-y growth rate between 2018 and 2024 (excluding the 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 the labor-intensive sectors (within manufacturing and services) to the total non-farm employment of 39 percent.
- The target of job creation for the labor-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 (6), 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:

$$employment_{t+n} = employment_{t} + (\Delta_{t+n} \times (N_{t+n} \times (Shareftrained_{t+n} - Shareftrained_{t})))$$

The number of formally trained workers required in time $t+n$, denoted as x_{t+n} is obtained by rearranging Equation (6). We use the following expression:

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

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 the effect in year t+n.
- $Shareftrained_t$ is share of formally trained workers 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 9) suggest that, in order to meet the *Economic Survey* target—adjusted for the labor-intensive manufacturing and services sectors—the share of the formally trained workforce should increase to around 20 percent by 2030, as compared to 5.4 percent 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 percent 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 that all non-farm jobs are created in the labor-intensive sectors within manufacturing and services, the required increase is much higher.

TABLE 9. Cumulative Addition to Jobs in the Labor-intensive Sectors (Including Both Manufacturing and Services) If Adjusted *Economic Survey* Target Is Met

Scenario	*Employment in Labor-intensive Sectors in 2023–24 ('000s)*	*Employment in Labor-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), Ministry of Statistics and Programme Implementation 2019-2024; Authors' calculations.

Note: i. The classification of labor-intensive sectors is based on a high labor-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 the labor-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 labor 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 percent of the 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 the labor-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 percent, relative to the existing scenario. On the supply side, we show that increasing the share of the skilled workforce by 12 percentage points through investment in formal skilling could lead to more than a 13 percent increase in employment in the labor-intensive sectors by 2030.

On average, labor-intensive manufacturing accounts for 44.1 percent of total manufacturing employment, while labor-intensive services account for 54.2 percent of total services employment. Combined, labor-intensive sectors constitute 51.3 percent of the 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 the labor-intensive industries therein.

We underline the need for a multi-pronged approach to increase production capacity in the labor-intensive manufacturing and services sectors, delineated below:

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 the 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 the Manufacturing and Services Sectors:* The Central Government has recently introduced the new version of the Production Linked Incentive (PLI) scheme. However, the PLI scheme is primarily focused on expanding the production of high-value products with backward-linkages, which require high-skilled, specialized labor and are relatively less focused on the low and middle-skill labor-intensive sectors. Specifically, over 50 percent 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 industries. Hence there is a mis-match between the weight of the budgetary allocation and the potential for employment creation.

   The cases in point are the textiles and footwear industries that have high labor intensity but lower exports than India's potential. Relatively lower U.S. tariffs than those on competitors such as Bangladesh and Vietnam can boost India's textiles and garment exports. In the services sector, hotels and tourism have seen slow growth in foreign visitors and particularly poor recovery post the pandemic. Here again, a policy-driven focus on attracting both foreign and domestic tourists is required. In addition, the opportunities in the labor-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 Labor Regulations:* Data show a persistent and steady decline in the labor intensity of production technology across sectors. This deepening of the capital intensity of the production process, particularly in and including the labor-intensive manufacturing and services industries, is likely to continue and increase with the advent of Artificial Intelligence (AI). We cannot ignore the long-standing issue of loosening our labor regulations that artificially inflate the cost of labor 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 labor to circumvent labor regulations. This underlines the need to allow more flexible hiring practices. The onus of adopting flexible labor 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 the demand for their products. Our analysis of the Annual Survey of Unincorporated Sector Enterprises (ASUSE) data on unincorporated non-agricultural establishments shows that access to credit can lead to a significant increase in the GVA of an enterprise, and thereby in 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 labor force is not only more likely to increase economic output, but also more likely to be productively employed. Thus, the productivity and quality of our workforce have to be increased significantly to address the constraints in the supply of labor. The government has emphasized and increased investments in vocational skilling, with the doubling of allocation for the Ministry of Skill Development and Entrepreneurship (MSDE) allocation from Rs 3,241 crore to Rs 6,017 crore in the 2025-26 Budget. The Skill India Mission, supported by the Pradhan Mantri Kaushal Vikas Yojana (PMKVY), Jan Shikshan Sansthan (JSS), 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 percent 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 as 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 services 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 (for example, dual VET systems in Germany, Austria, and Singapore, the co-op system in Canada), combine classroom learning post high school 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 that 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 the increased adoption of machinery. In a recently concluded RCT in Delhi and Bengaluru, Afridi (2025) shows 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 the portability of workers' skill certification across employers and sectors.

   Our simulation results indicate that 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, as compared to 14.0 million when only the share is enhanced—resulting in 800,000 additional jobs. This corresponds to a 14.2 percent increase in employment, as opposed to 13.4 percent under the scenario where only the 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 the worker turnover is low and retention is high.

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

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Comments and Discussion*

Chair: S. Mahendra Dev

Economic Advisory Council to the Prime Minister

Deepak Mishra

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Farzana and her team have done an excellent job documenting and distilling the stylized facts from the Periodic Labour Force Survey (PLFS) on India's labor market. This is one of the most authoritative analyses I have seen in recent years. My congratulations to the entire team.

As I was going through the paper and preparing my comments, I felt like the person who was asked to clean up the beach, while at the same time being warned that a six-meter tsunami is about to hit. So rather than spending my energy collecting the rubbish on the beach—by which I mean, commenting on the usual labor-market issues—I have decided to focus on the incoming tsunami: the impact of Artificial Intelligence (AI) on India's labor market. Therefore, I will talk about how to create plentiful jobs in the age of AI—a somewhat counterintuitive narrative—and, along the way, weave in some of the key insights from Farzana's paper.

Before I begin, I want to thank NCAER and the organisers for this invitation. It is a real pleasure and an honor to be part of such an esteemed panel—and to speak before such a distinguished audience.

When it comes to predicting the impact of AI on jobs, whose judgment would you trust more: Dario Amodei, co-founder and CEO of Anthropic, one of today's leading AI companies, or Daron Acemoglu, the prolific economist and 2024 Nobel laureate?

The reason I ask you to choose between these two gentlemen is that they sit at opposite ends of the debate on AI's impact on jobs. Dario Amodei warns that AI could eliminate up to half of all entry-level white-collar jobs and push unemployment to 20 percent within the next one to five years. That is nothing short of a labor-market tsunami on a scale none of us have witnessed in our lifetime.

* To preserve the sense of the discussions at the India Policy Forum, these discussants' comments reflect the views expressed at the IPF and do not necessarily take into account revisions to the conference version of the paper in response to these and other comments in preparing the final, revised version published in this volume. The original conference version of the paper is available on NCAER's website at the link provided at the end of this section.

Daron Acemoglu, by contrast, estimates that only about 5 percent of current jobs are at risk of being replaced, and even those may not see major disruption from AI over the next decade. His view is far more moderate—well within the range of labor-market changes we have seen before. If we believe Acemoglu, then the impact may not even rise to the level of a typical business-cycle downturn.

So, will the impact be massive or modest? If there were more time, I would have loved to take an informal poll of the audience. But since we cannot do that, let me offer my own answer: neither. That's because economists, technologists, and even the most influential thinkers have been more wrong than right when predicting the impact of technological progress on jobs.

Many of you may recall John Maynard Keynes's famous letter to his grandchildren, written in 1931, where he warned of a new "disease" sweeping through the world economy: technological unemployment. He defined it as unemployment caused when new ways of economizing labor advance faster than our ability to create new uses for labor. Yet nearly a century after Keynes wrote those words, global labor markets continue to show healthy demand for workers, and unemployment rates in many countries—including India—remain at historically low levels.

And then we have Isaac Asimov—author of some of the bestselling science-fiction books—making predictions in 1964 about what the world would look like in 2014. He imagined a future in which very few routine jobs remained because machines would perform them better than humans. His writing reads almost as if it were written for the AI age. Asimov warned that humanity would suffer from a "disease of boredom," and that only the fortunate few engaged in creative work would form the new elite—because they alone would be doing more than merely serving machines.

Thankfully, both Keynes and Asimov have been proven wrong. Like them, many of us fall into the trap of predicting mass unemployment every time a new technology arrives. I, too, have been guilty of this. In 2016, when the World Bank President visited India, he declared that "automation threatens 69 percent of jobs in India," citing the 2016 World Development Report (WDR)—a report I had helped produce—as the basis for his claim. The figure taken from that WDR does show that from a technological standpoint, two-thirds of all jobs in India are potentially automatable. But the WDR also clearly states that the actual impact would be moderated by factors such as lower wages and slower technology adoption. So yes, 69 percent is technically the right number, but it comes with a long list of caveats—and, importantly, with no timeline for when such displacement might occur. Predictably, none of that nuance survived. The caveats were ignored, the timeline was forgotten, and even the World Bank President's own speechwriters could not resist the temptation of turning a conditional estimate into a headline-grabbing prediction.

Why do we fall for these Luddite-style fallacies? There are two main reasons for this. First, it is far easier to estimate the jobs that might be replaced by machines than to imagine the jobs that will be created by technological innovation. Job losses are visible and immediate; new jobs are uncertain and often emerge in sectors that do not exist today. Second, we focus almost entirely on the jobs created by the "upside" of technology—new industries, new products—while overlooking the large number of jobs generated from dealing with the "downside" of technological change, that is to manage, regulate, repair, supervise, and mitigate all the risks emerging from mass adoption of AI.

This is the crux of my argument: technology creates jobs not only through its benefits, but also through the risks it introduces. One of the best examples of risk mitigation generating large-scale employment is the rise of India's IT industry. The sector took off during the Y2K crisis, when there was fear that computers would interpret the "00" as year 1900, not year 2000, potentially crippling IT systems worldwide. Indian IT professionals painstakingly combed through millions of lines of legacy code to fix this vulnerability and, in the process, helped avert a global IT meltdown. This exercise in risk mitigation effectively gave birth to India's modern IT industry—an industry that has created nearly 6 million high-paying jobs and another 10 million jobs indirectly.

Here is a simple way to visualize how job creation and destruction unfold over a cycle of technological progress. In Stage 1, we see a sharp productivity boom—this is when technology largely substitutes workers. Firms need fewer employees, and job creation dips. This is the phase we are currently experiencing with AI. As technology automates more tasks, however, prices fall, incomes rise, and consumers begin to demand new goods and services. This triggers Stage 2, when technology creates new tasks, new activities, and entirely new industries, producing a wave of new jobs. Once technology becomes widely diffused, Stage 3 emerges: risks become visible, prompting investment in oversight, governance, security, safety, and compliance. These risk-mitigation efforts create yet another round of job growth. In short: job losses in Stage 1, job creation in Stage 2, and often even more job creation in Stage 3.

This is not an abstract theory—it resonates with real-world experience. Take the agricultural revolution, which led to increased availability of food and sharp decline in food prices. The biggest risk that emerged from that revolution was over-consumption—leading to obesity and a host of related health problems. To manage these risks, society needed doctors, nurses, nutritionists, wellness coaches, fitness trainers, and an entire healthcare ecosystem, in other words, an array of jobs that simply would not exist in a food-scarce world. Risk mitigation itself created whole new sectors of employment.

If we look back over the past 100-150 years, the pattern becomes unmistakable. At the start of the twentieth century, the United States had roughly 12 million farmers; today that number has fallen to about 0.5 million. Yet during this same period, the economy created millions of new jobs—around seven million to mitigate the risks from over-consumption. Not all of these can be directly attributed to falling food prices, but a large share certainly can. And beyond these are countless additional jobs that rarely get counted, created specifically to manage the risks and consequences of cheap, abundant food.

Following the information revolution—and the dramatic reduction in the cost of producing and accessing information—we now over-consume information in every form. This over-consumption brings its own risks: fake news, misinformation, loss of privacy, identity fraud, mental-health stresses, and many other vulnerabilities. You may be surprised to know that, by some estimates, we now have as many content moderators as coders.

At the same time, technology is diffusing faster than ever before. This means that risk mitigation must begin much earlier in the cycle of technological change than was previously the case. Technology diffusion curves have become increasingly steep over time—implying that risks emerge sooner and need to be addressed at earlier stages. This opens a strategic opportunity for India: as the rest of the world looks for ways to mitigate the risks posed by AI, we can proactively build education, training, and upskilling programs that prepare our workforce for these new risk-related jobs.

Since Mr Manish Sabharwal is here, let me use his company, TeamLease, to illustrate how India can create plentiful jobs in the AI age. Today, TeamLease employs lakhs of physical security guards. And what do these guards protect? Their clients' physical wealth—gold, cash, and other valuable assets. But by 2050, the primary wealth will mostly be in digital assets. That means every household will need a digital asset guardian. As Dr Mahendra Dev mentioned earlier, digital jobs tend to be among the highest paying. So, as physical security roles gradually give way to digital asset guardianship, we should see the emergence of new and better-quality jobs.

We are already seeing this shift. Look at the job titles now appearing on LinkedIn. We have always had auditors, but companies are now recruiting AI risk auditors. We have always had specialists, but firms now need AI safety specialists, model evaluators, and alignment testers. In the coming years, lakhs of people will hold such job titles. So, the question we should be asking is not whether AI will create more jobs than it eliminates, but whether India is prepared to capture the millions of new jobs that AI will bring.

Let me conclude with the key takeaways of my presentation. History is littered with stories where experts have misjudged the impact—both the direction and the scale—of new technologies on employment. Each major technology breakthrough has been accompanied by panic and paranoia, fueled by the persistent belief that technological progress destroys more jobs than it creates. Yet, time and again, technology has unlocked far more opportunities than it eliminated. What is often overlooked is that new technology generates employment not only by unlocking new opportunities but also by generating new roles to manage and mitigate the risks it introduces. India is uniquely well positioned to benefit from this dynamic. By becoming a global hub for AI risk mitigation, India can create a vast range of high-quality jobs—jobs that barely exist today but will soon be indispensable.

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It is always a pleasure to be here and I have got multiple discussions to do over three days. So, I will keep this short.

There is always a tension in these ten-minute discussion sessions between discussing the paper and expanding the discussion to what to do about the issues raised in the paper. I am going to focus more on the second. At a high level, it is a very useful paper. It summarizes a lot of key facts and I also agree with a lot of the key messages in it, particularly the centrality of focusing on labor-intensive sectors. It sounds obvious but it is important to keep reiterating this because so much of the pattern of Indian job creation is capital-intensive and there is a whole range of legacy reasons for that. If you look at how states compete for investment, the number one tool everybody seems to use is different kinds of incentives, and companies are very smart in terms of pitting states against each other to get the best deal they can, and that is a deal that is going straight into the bottom line of capital as opposed to helping labor locally. So, thinking about policies with labor at the core of it is absolutely central to how they need to think about jobs and inclusive growth. I also agree completely on the piece about skills.

I have minor suggestions for the paper. I think the focus on job quality comes a little late in the paper, as a lot of the early focus is just on jobs. As has been said again and again, we do not have a jobs crisis, we have a wages crisis. Since most people in India cannot afford to be unemployed, it means that the real challenge is to improve job quality, which means improving wages, benefits, and elements of job security. So, it is not just the lack of jobs, it is the precarity of the jobs in the labor markets. These are things that matter directly for human welfare. Of course, everybody wants good wages and benefits, but you can only afford this sustainably if the value created by the employees is higher than the cost, which means that you have to push up productivity.

In the long run, wages depend on both productivity and bargaining power. So, if you think about moving a peasant onto a factory floor and productivity goes up, the question is how is that productivity split between capital and labor? And that is going to depend on whether capital or labor is the scarce factor. Thus, in settings where capital is the scarce factor, more of those benefits will accrue to capital, and that is consistent with the patterns we see but the good news is that on average, wages and benefits seem to track productivity very closely. This means that as a first order, we can focus on productivity and assume that markets for the most part are competitive, and that wage is a tracking marginal product, which motivates the whole analysis.

I have some quibbles about some aspects in the paper that I do not think are adding much value, like the correlations between output per worker and GDP per capita. I think what the paper is trying to do is open up the conversation, but we would really benefit from getting a bit more into the black box of both firms and government.

The single main topic I want to focus on is something that I do not think enough people talk about, which is the long shadow of public-sector labor markets on every problem that we are talking about. When we talk about problems in skilling, we know that the problem is that we have a dysfunctional education system, and we think this is because we are not spending enough and there are some issues of governance but it is much deeper than that. And what I want to focus on is the core challenge of service delivery in India.

Everybody knows that public education is weak, public health is weak, anybody who can afford to go to the private sector goes to the private sector. But the core problem is that the Indian Government is the most under-staffed in the world. We have the fewest employees per capita relative to any major comparable country: one-tenth of Scandinavian countries, which are high-tax welfare states; one-fifth of the U.S.; and one-third of China. So, it is not a surprise that we are unable to deliver services effectively. That is because we do not have enough employees. But why do we not have enough employees? The flip side of that argument is that is because Indian government employees are the most overpaid in the world, barring at the top, where people are underpaid, and that is because there is massive wage compression in the public sector. So, the top 2 percent of government jobs are probably paid much less than what the market would pay for that same set of skills, but the bottom 95 to 98 percent are massively overpaid. This is data from one of my studies around 2010, where we see that the average government school teacher makes about six times more than a private school teacher in Andhra Pradesh. The reason why this is such a big problem is that we may think we need to pay high to get productivity, but the bad news is that there is absolutely zero link between pay and productivity in the public sector.

We have got study after study showing that even doubling teacher pay or unconditional pay increases have absolutely no impact. In contrast, we have study after study showing that locally hired staff who are less qualified but connected to the community perform at least as well, and this is mainly driven by higher accountability in connection to the community. I have been studying teacher and doctor absenteeism for 25 years, but now when gram chikitsalayas show that the doctor has not shown up in years, this issue has come into the broader public domain. Our model of public-sector staffing suggests that we need highly qualified people hired through a civil service exam, but we post them to areas that they have no desire to go to. There are thus enormous distortions. We have got study after study showing that basically augmenting staff with locally hired staff, especially in the areas of early childhood education and health, can get dramatic improvements.

Citing just one example, we have a study in Tamil Nadu where we did an RCT last year on augmenting state capacity. Just hiring an extra anganwadi worker focused on preschool education led to a dramatic improvement in both the learning outcomes and the reduction in malnutrition. And we estimate the Return on Investment (ROI) on this is about twenty times, signifying a 2000 percent ROI based on what the global estimates are but where does all of our money go? It goes into increasing salaries of incumbent staff because politically the incumbents are always more powerful than the outsiders. The direct problem of this is obviously weak state capacity but I think what people do not appreciate enough is that it is not just that this weakens the state; it has massive costs for the overall economy.

The structure of this very high public-sector pay creates a massive problem of misaligned incentives and corruption in recruitment. Today in Bihar or Jharkhand, it has become impossible to run public service exams even with military election-level security because the benefits of leaking that paper are so high that it has badly distorted the market. All the force in the world cannot deal with those kinds of market incentive distortions that have been created with the structure of the labor markets. And the skill mismatch in the government is so massive because people are applying for any possible government job, including jobs as forest guards, as teachers, as railway guards, it does not matter as long as it is a government job. All this directly hurts state capacity, but what I want to talk about are the larger distortions for the broader economy on the General Equilibrium (GE) effects.

I think one of the most significant factors we do not understand and appreciate enough is that the single biggest source of educated unemployed youth in India is the structure of public-sector labor markets. There is a depressing but important recently published study in Tamil Nadu showing that there are around 80 percent unemployed educated youth in India, which is because they are writing government exam after government exam after government exam. What is worse than that is the low demand for skills.

So, I fully agree with Farzana that you need more skilling. However, you cannot solve the skilling problem by building more training centers, and as Lant Pritchett famously said, “Demand and supply matter for outcomes as much as gin and tonic matter for getting you drunk.” So, while you can push supply, there is no demand for skills and that is because people drop out of skilling programs as they would rather attempt the government job lottery. The result is this crazily dysfunctional labor market where on one side, you have millions of college graduates with no jobs, and on the other side, you have companies saying, “I want people and I cannot find them.” And that is because our education system produces candidates who take exams and have no skills because the most lucrative employer in the economy only cares about exam-taking skills. All you need to do is crack the exam and there is nothing there about whether you have real-world skills. That is the sense in which the structure of the public-sector labor market introduces these massive distortions. Everybody says, "There are 200 applicants per government job, which means that the private sector is not creating jobs." But that is not true—the private sector creates jobs but at market wages. The problem, therefore, lies not in the private sector, but in the public sector, which is completely out of tune with market reality.

The research on teacher training shows that there is zero correlation between having a training credential and effectiveness in the classroom, and that is because most of these degrees focus on history, theory, philosophy, and sociology of education as opposed to how to actually teach in the classroom. So, if there was one thing I would advise the government to do in the next two years and single-mindedly focus on because it addresses so many of the issues is to re-imagine our entire skilling ecosystem to ensure that it is based on apprenticeship and practical skills. The idea is to create 2-4-year modular district level programs that combine theory and practice, where you get three months of theory every year and nine months of practice. The need is to focus on education, health, and public safety, the three largest sectors of government employment. You should target candidates from under-served areas, and the government should fund the training and provide a modest stipend. The trainees can be placed in local schools, clinics, or public police stations supporting senior staff and acquiring real-world skills, and a professional diploma or degree at the end of the program that is recognized by both the government and the private sector.

This is very different from Agniveer because in Agniveer, you do not have an equivalent private sector employer. There is no private sector demand for deploying lethal force, which is what the army teaches you to do, whereas in the areas of public safety, teaching, and health, the private sector employs four times more people. So, when you are doing this kind of skilling, you can also link it with the private sector and create a pathway for jobs. And eventually for government recruitment, all you need to do is tweak the recruitment rules to say that you will still have competitive exams and competitive recruitment but you provide a little bit of extra points for time spent in that sector. In this way, you are rewarding interest and commitment to that sector as opposed to taking government job exam after exam after exam. This essentially solves a whole bunch of problems.

Going back to what Farzana was saying about the centrality of skilling, it augments state capacity for staffing. So, why are we not able to get even 50 percent of kids who are able to read at the end of five years at a Grade 2 level? That is because apart from the problem of absence, the other problem is that many schools have just one teacher or two teachers teaching five grades. Thus, you have got multi-grade teaching and what the apprentice model allows you to do is augment that capacity to do small group instruction, which has widely proven to be effective. This gives you a cost-effective expansion of state capacity, it addresses geographical mismatch, you get a much better long-term job fit, and there is a positive economic and social impact of reducing youth unemployment, boosting employability in the public and private sectors, and strengthening community service delivery.

This is also important for gender and in terms of enhancing female labor force participation. For instance, Tamil Nadu did perhaps the world's most ambitious post-forward learning remediation program called "Illam Thedi Kalvi", wherein two lakh young women were hired for bringing education at the doorstep, where they did supplemental education for 60-90 minutes a day. The amazing thing was that this paid a stipend of Rs 1000 a month, and still there were four applicants per job. When these women were interviewed, they said that more than the money, they value the dignity, the respect, and the ability to leave the house in the evening and have some kind of connection with the community. Thus, there is a lot of latent labor supply that can be unlocked if you start creating employment opportunities locally, which would be a win-win situation in multiple ways.

General Discussion

Martin Wolf wanted to know whether caste was in any way a significant factor in the operation of the Indian labor market and its effectiveness versus other similar countries.

Rana Hasan pointed out that it would be helpful to look at the state-level stuff. He highlighted the need to analyze the reasons for the differing performances of various states. For instance, why does Tamil Nadu do so well, versus the next tier of states where land and labor prices are relatively cheap? He also noted that the government is funding a lot of the programs related to the supply side of skills. However, while everyone agrees that they should be based on a Public Private Partnership (PPP) model, the devil is in the details. How that PPP model is structured is critical.

Laveesh Bhandari raised two issues: first, on the need for discussion on the government program of Mudra, which has seen a large outflow of credit given to the so-called small entrepreneurs, which could also account for the rise of female entrepreneurship, as highlighted in the paper. And second on labor laws, which, in some sense, signify an institutional barrier that critically impacts the economy.

Sam Asher wondered that given the massive gaps in wages across states, across sectors, and across the rural-urban divide, what hurdles were preventing people from moving out of agriculture and into more productive jobs in the cities.

Pravin Krishna posed a question on the particular graph in the paper which showed India stuck out as a bit of an outlier with a high fraction of workers who were trained but not employed in the education sector. This points to a demand-side issue, rather than an artifact of differences in what training actually means across countries, and that training on paper is different from how it actually pans out in practice.

Franziska Ohnsorge stated that the issue of labor markets is a long-standing one. She asked two questions: the first was as to why there were no recommendations on streamlining the role of the government in education, on ways of reducing the gap between private-sector and public-sector salaries and reducing the number of times people can take exams to enter employment in the public sector, or forcing people to spend some time outside in a private sector before they are allowed to apply for government roles. Her second question focused on the ongoing upheaval in the global trade network, and how India could capitalize on this situation to boost outcomes for its labor-intensive industries.

Vidhya Soundararajan argued that the issue of people moving out of agriculture into manufacturing services was actually about structural transformation. It is imperative to analyze how land market reforms could drive such a transformation.

Lata Venkatesh highlighted a couple of disparate points. The first, taking off from Martin Wolf's query on the role of caste in shaping outcomes in the Indian labor market, was her suggestion that anecdotally people seek desk jobs, which has the potential to distort the labor market. The second issue flagged by her concerned the juxtaposition of the dilemma, on one hand, of large organizations in the formal sector that have vacancies for which they are willing to pay lucrative wages but cannot find the right people to fill them, versus workers who cannot find the formal-sector jobs they are looking for. She also asked whether now that India had an ostensible tariff advantage over other countries, with its 10 percent tariff bracket as opposed to the 30 percent bracket for other nations such as China, Vietnam, and Bangladesh, would that open up opportunities for Indian workers in the labor-intensive sectors such as footwear and textiles, among others?

Ratna Sahay asserted that an important aspect of the labor market was being overlooked as the aggregate or sectoral figures being discussed were not distinguishing between female and male employment, and female and male labor force participation. There is a low-hanging fruit which is related to the labor laws. She also expressed concern at the fact that India has not formalized part-time employment while the rest of the world has, which entails a huge difference for women, who are equally, if not more, qualified as their male counterparts in the country. The phenomenon of women enhancing their education and skills but not translating them into formal employment signifies wasted opportunity. The situation is exacerbated by the fact that many women do not work because of the lack of flexibility in employment and lack of compensation for part-time employment. The second factor relates to the significantly larger care responsibilities that women have relative to men. She maintained that if these two issues could be addressed in India, it would lead to an exponential increase in both female employment and aggregate productivity in the country.

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