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India's Employment Prospects: Pathways to Jobs

December 2025

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Foreword

India's growth trajectory is underpinned by a distinct demographic advantage, but this is increasingly shadowed by persistent challenges in generating employment, especially in creating enough productive jobs to meet the demands of its expanding workforce. Although employment pressures during structural transformation are common among all developing nations, the magnitude and immediacy of India's employment challenge stand out globally, driven largely by the sheer size of its working population.

Against this backdrop, NCAER undertook this study to explore the evolving contours of India's labour market, with a focus on employment; quality of employment; sectoral multiplier effects; patterns of occupational mobility; and, the structural barriers hindering more job creation in the country.

Using nationally representative surveys and administrative data, this report evaluates whether India's current growth trajectory can generate not just more jobs, but employment that is better in quality, more secure, and broadly inclusive. As the country advances toward the Viksit Bharat 2047 vision, bolstered by its demographic dividend and growing digital capabilities, the need is clearly to create a future-ready labour market that is resilient and equipped to unlock the full potential of its people. The analysis in this report highlights that expanding labour-intensive manufacturing and services holds significant potential to close much of India's employment gap. These sectors already contribute over half of the jobs in the manufacturing and services sectors, and strong inter-sectoral linkages could substantially boost employment under high-growth scenarios. On the supply side, increasing the proportion of formally skilled workers and enhancing the quality of training could further accelerate the growth of labour-intensive sectors by 2030.

The report calls for comprehensive policy changes to realise this potential. On the demand side, reforms should aim to: boost domestic consumption; redirect Production Linked Incentives (PLI) toward labour-intensive sectors; improve access to credit; and, simplify labour regulations. On the supply side, vocational education needs a fundamental transformation, which includes integrating Vocational Education and Training (VET) into early schooling; creating pathways to higher education; aligning curricula with industry demands; strengthening public-private partnerships; and, increasing public investment to match global standards.

I would like to acknowledge the dedicated efforts of the NCAER study team, led by Professor Farzana Afridi, in conducting this important study. It is hoped that the insights and findings presented in the report will meaningfully support the government's ongoing initiatives to enhance employment and realise the vision of Viksit Bharat by 2047.

Anil K. Sharma
Secretary and Operations Director
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Acknowledgements

First and foremost, we would like to express our deep gratitude to the former Director General of NCAER, Dr Poonam Gupta, whose motivation and deliberations led to the initiation of this study in January 2025. Dr Gupta's insights helped shape the macro-analytical framework of our work and focus on key metrics during the planning stage of this report.

We sincerely thank Professor Bornali Bhandari, Mr Devender Pratap, and Mr Ajaya Kumar Sahu from the *Agriculture*, *Industry*, *Trade*, *Technology & Skills* team at NCAER for their valuable inputs in estimating employment multipliers and for providing us with the updated Input–Output Table for 2018–19.

We are deeply grateful to, Dr S. Mahendra Dev, who had chaired the discussion of an earlier version of this report at the India Policy Forum 2025 Conference and the three discussants—Dr Deepak Mishra, Dr Karthik Muralidharan, and Mr Manish Sabharwal, for their insightful comments and constructive feedback, which have substantially enriched the report.

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We are also grateful to the Secretary and Operations Director at NCAER, Dr Anil K. Sharma, for his consistent support and for overseeing the logistical aspects of this work to ensure its smooth execution.

Finally, we would like to thank the editorial and communications team at NCAER—Ms. Anupma Mehta, Ms. Devanshi Mankotia and Mr. Praveen Sachdeva—for their dedicated efforts in editing, formatting, and designing the report for release.

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Executive Summary

India's economic trajectory has seen an impressive run over the last few decades, but concerns are rising over the country's ability to productively engage a large and growing working age population. Recent increases in employment are primarily due to the rise in self-employment, while transition to a skilled labour force has been slow, highlighting the need for creating not just jobs but 'good' jobs. Furthermore, the rising capital intensity of production technology necessitates the development of a skilled and productive workforce to increase the share of labour in aggregate value added in the economy. In the race for a US$ 7 trillion economy, India needs to urgently overcome bottlenecks to increasing both the quality and quantity of workforce participation and sectoral labour productivity.

In this report, we underline the key role of the manufacturing and services sectors, particularly the more labour-intensive sub-sectors therein, as key drivers of job creation in India. Chapter 1 highlights structural constraints on both the demand and supply side of the labour market that hinder progress towards attaining the employment goals for *Viksit Bharat.* For this we utilise several country-level databases to underline India's performance on key employment metrics relative to countries at comparable levels of economic growth. In the subsequent chapters, we project potential job creation between 2025 and 2030 under varying economic growth scenarios, if these constraints are loosened. .

Chapter 2 focuses on the demand for labour. We discuss the structural aspects of job creation and explore how sectoral patterns of production and investment influence labour demand in India. We compute employment to output elasticity for the manufacturing and services sectors, as well as for the relatively more labour-intensive sub-sectors, and find a consistent fall in labour intensity across the manufacturing sub-sectors (viz., garments and textiles, and electronics) but significant concomitant increases in the services sub-sectors (viz., education, health, and finance). Next, we calculate industry-specific employment multipliers to estimate spillover or indirect employment creation through the backward linkages of the labour-intensive manufacturing and services sectors.

Simulations to assess the impact of higher investment in labour-intensive manufacturing and services for achieving moderate growth in Gross Value Added (GVA) indicate that if the manufacturing and services sectors grow at 8.2 per cent and 9.0 per cent annually, an aggregate GVA growth rate of 8 per cent can be achieved by 2030. This corresponds to an annual addition of 71,543 (3.9 per cent) and 2,79,130 (2.4 per cent) new workers in the manufacturing and services sectors, respectively. To further estimate the multiplier effects of inter-sectoral linkages, we project that a moderate growth in Gross Output (GO) of the relatively more labour-intensive sub-sectors within these two sectors will lead to multi-fold job creation by 2030, that is, 53 per cent in the textile, garments, and related industries in manufacturing, and 79 per cent more jobs in trade, hotel, and related services, driven not only by direct employment creation but also by spillover effects throughout the supply chain.

In Chapter 3, we address the supply side factors that impinge on job creation. We find that medium skilled jobs dominate employment growth, especially in services whereas manufacturing remains low-skill intensive. Despite a fall in the share of untrained workers between 2018 and 2024, as of 2024, only 4 per cent of workers had received formal skill or vocational training. Informal training is more common but does not necessarily translate into high-skill, regular employment. Formal vocational training, on the other hand, significantly increases the probability of securing high-skill, salaried jobs.

Simulations show that increasing the formally skilled workforce under the moderate growth scenario leads to significant job gains in the labour-intensive sectors. Increasing the share of the skilled workforce by 9 percentage points through investment in formal skilling could generate 9.3 million jobs, amounting to a nearly 9 per cent increase in employment in the labour-intensive sectors by 2030. These results suggest that combining a higher share of formally trained workers with improvements in training quality could generate additional employment gains of around 100,000 jobs.

Despite recent policy efforts, India's Vocational Education and Training (VET) system continues to face deep structural challenges, including under-utilised seats, poor placement rates, vacant instructor posts, weak industry linkages, and a persistent perception of vocational education as a fall-back option. These gaps explain why training outcomes remain weak, with many VET graduates still employed in informal and low-paying jobs. International experience shows that early integration of VET; ensuring defined pathways to higher education; and strong employer engagement may be associated with better labour market outcomes. India also lags in VET investment, having allocated only around 3 per cent of total education expenditure to vocational training in 2021 as compared to an expenditure of 10–13 per cent incurred on VET institutions in countries such as Germany (2020), Singapore (2021), and Canada (2020).

Chapter 4 of the report points out that even as India's informal (non-agricultural) enterprises play a crucial role in creating jobs, they face significant challenges. An overwhelming majority of these enterprises are Own Account Enterprises (OAE), which tend to be low in productivity and hire none or very few workers. Among Hired Worker Enterprises (HWEs), the services sector employs overall more workers than the other sectors, but each manufacturing enterprise hires more people, on average. This underscores the need to tap into the potential of manufacturing because when OAEs in this sector transition into HWEs, they generate larger employment gains per enterprise. Raising their productivity is, therefore, the key to enabling this shift, which can both create more jobs and foster entrepreneurship. Evidence from the analysis also shows that access to digital technologies and credit is strongly linked to productivity, measured through GVA. In fact, a 10 per cent increase in the GVA of these informal enterprises is associated with the creation of nearly 5.6 million new jobs.

We conclude the report with policy prescriptions to boost aggregate demand and investment, and enhance workforce productivity in Chapter 5. Our demand-side simulations indicate that strengthening employment opportunities in both the manufacturing and services sectors could help sustain GDP growth at around 8 per cent, consistent with the vision of *Viksit Bharat*. At the same time, labour market trends highlight a paradox: while the formal sector shows rising labour elasticity of output, the informal sector is witnessing a decline. This shift, alongside the growing reliance on contractual workers, emphasises the need for labour codes that strike a balance between flexibility and security. The policies could be flexible enough to encourage employers to expand full-time hiring while ensuring adequate protections and stability for workers. In this context, targeted policies for the garment and textile sectors, such as Tamil Nadu's 2019 Textile Policy, which combine worker housing, skilling schemes, and the development of Integrated Textile Parks to foster industrial clustering, offer a replicable model for generating large-scale employment in labour-intensive manufacturing while moving up the value chain.

On the supply side, India's workforce could benefit greatly from upskilling to ensure future market readiness, particularly with the advent of new technologies. This requires a shift from short-term, fragmented training to a systemic overhaul of education, necessitating various recommendations, as suggested below.

First, integrate VET into early schooling, as envisaged under the NEP 2020, though progress has been slow. *Second*, fast-track reforms to operationalise the National Credit Framework, creating clear progression pathways and establishing a national board for recognised certifications. *Third*, improve training quality by aligning courses with local industry demand through regular market assessments, expanding National Skill Training Institutes (NSTIs), accelerating instructor recruitment, and strengthening ITI grading by incorporating trainee feedback. *Fourth*, scale-up public–private partnership models by leveraging public infrastructure with private expertise, involving Micro, Small and Medium Enterprises (MSMEs), and strategically using Corporate Social Responsibility (CSR) funding to boost industry relevance. *Fifth*, increase public spending on VET and improve institutional viability by linking funding to performance and granting greater autonomy to generate revenue.

Additionally, targeted interventions are needed to unlock employment potential in specific sectors. In manufacturing, reorienting production-linked incentives towards labour-intensive industries such as textiles, garments, footwear, and food processing can yield higher job multipliers than the current focus on capital-intensive sectors. In services, policy support for tourism, education, and health can create large-scale, inclusive employment. Complementary measures, such as state-level industrial clustering, bilateral trade agreements to expand market access, and improved credit access for MSMEs, will be critical to scaling-up job creation. The Employment Linked Incentive (ELI) Scheme, if paired with stronger safeguards for retention, periodic evaluation, and integration with skilling initiatives, could emerge as an important fiscal instrument to nudge formalisation and sustain new employment.

Thus, India's employment strategy must go beyond setting aggregate growth targets to attaining a calibrated mix of demand-side and supply-side measures that directly incentivise labour absorption. On the demand side, this entails stimulating domestic consumption, reducing hiring disincentives through more flexible labour regulations, and expanding credit and the ease of doing business. On the supply side, it requires a systemic overhaul of vocational education with early VET integration, national credit portability, stronger industry partnerships, and greater investment in training quality. Such a multi-pronged policy approach can bridge India's jobs gap, ensure durable formal sector participation, and translate rapid economic growth into secure and productive employment for millions.

Abbreviations and Acronyms

ASI	Annual Survey of Industries
ASUSE	Annual Survey of Unincorporated Sector Enterprises
CAGR	Compound Annual Growth Rate
CWS	Current Weekly Status
ETD	Economic Transformation Database
GDP	Gross Domestic Product
GST	Goods and Services Tax
GVA	Gross Value Added
G(V)O	Gross (Value) Output
HWE	Hired Worker Enterprises
(ILO) STAT	(International Labour Organization) Database on International Labour Statistics
IMF	International Monetary Fund
I-O	Input-Output
ISIC	International Standard Industrial Classification
JSS	*Jan Shikshan Sansthan*
KLEMS	Capital, Labour, Energy, Materials and Services
L/K	Labour capital (ratio)
MSDE	Ministry of Skill Development and Entrepreneurship
NAPS	National Apprenticeship Promotion Scheme
NAS	National Accounting Statistics
NCO	National Classification of Occupations
NPI	Private Non-Profit Institutions
NPISH	Non-Profit Institutions Serving Households
NSO	National Statistical Office
NSS(O)	National Sample Survey (Office)
OAE	Own Account Enterprises
PLFS	Periodic Labour Force Survey
PMKVY	Pradhan Mantri Kaushal Vikas Yojana
PPP	Purchasing Power Parity
PWT	Penn World Table
RBI	Reserve Bank of India
RCT	Randomized Controlled Trial
SD	Standard Deviation
SHG	Self-Help Groups
SUT	Supply and Use Tables
USD	United States dollars
VET	Vocational Education and Training
WFPR	Work force participation rate
WPI	Wholesale Price Index

Chapter 1
India's Twin Challenges: Demand for Labour and Workforce Quality

1.1. Introduction

India's economic journey over the past three and a half decades has been widely acknowledged—marked by rising GDP growth, diversification into services, deepening integration and deregulation with international markets and admirable resilience in the face of geopolitical instability. The liberalisation reforms of the early 1990s set the foundation for sustained economic expansion, enabling India to emerge as one of the fastest-growing major economies in the world, with strong recoveries against the global crises of 2008 and 2020. With a projected GDP of 6.3 trillion USD by 2030 (IMF 2024) and expectations of becoming the world's third-largest economy by 2030 (Economic Survey 2024-25), India's growth narrative and its success in navigating macroeconomic disruptions with increasing policy maturity, continue to draw global optimism.

This progress story is anchored by a unique demographic advantage, increasingly accompanied by persistent challenges in employment generation, particularly in terms of creating sufficient and productive job opportunities for India's growing workforce.

India is not unique in facing employment stress during structural transformation—many developing economies experience friction as labour reallocates across sectors. But the scale and urgency of India's employment challenge are globally unmatched, largely due to its sheer demographic weight. The United Nations projects India's working-age population will continue to grow until the late 2040s, providing a limited window in which demographic advantage can be converted into an economic dividend. The absence of sufficient productive employment could turn this momentum into a drawback—manifesting in widespread underemployment, growing informality, and a disillusioned youth workforce (UNFPA, 2024; World Bank, 2024).

Since 2017–18, India's working-age population has grown by nearly 90 million, but the economy has created only about 60 million jobs in that period (PLFS, 2024). This translates to a shortfall of 5 million jobs per year, even as roughly 10–12 million people enter the labour force annually. Of those who do find work, only 1 in 4 enter the formal wage economy, with the majority absorbed into informal services, self-employment, or low-productivity agriculture (PLFS; ILOSTAT). These trends point to an employment structure that is increasingly fragmented and unable to offer quality work opportunities at scale.

Our jobs deficit is not just a matter of numbers—it reflects a deeper disconnect in structural transformation. Unlike the textbook pathway from agriculture to labour-intensive manufacturing and then to services, India has leapfrogged into the latter without building a broad industrial base. The share of manufacturing in employment has stagnated or declined in several states, and the sector is becoming more capital-intensive over time. As a result, India has struggled to absorb its surplus labour into higher-productivity sectors—a phenomenon described as "premature deindustrialization" (Rodrik, 2013). This deviation from the conventional growth-to-jobs trajectory has subverted the economy's capacity to create stable, semi-skilled employment for large segments of the population.

This is more evident among India's youth. Despite improvements in educational access, a large share of the young population remains "Not in Education, Employment, or Training" (NEET)—with rates reaching 39 per cent among young women and 10 per cent among young men, one of the highest globally (ILOSTAT 2024). Many youths face a triple burden: skill gaps, high reservation wages, and spatial mismatches that reflect the divide between aspirations and reality, especially for first-time labour market entrants.

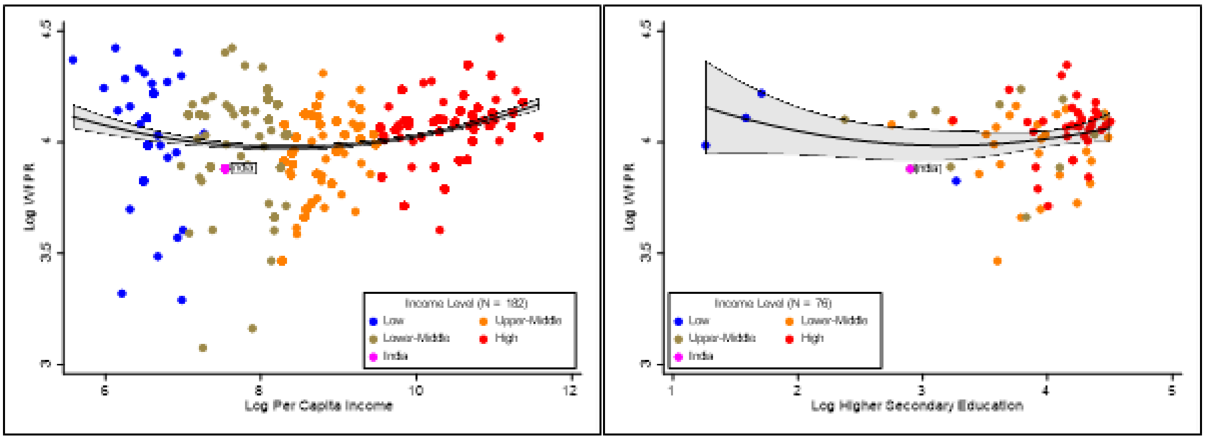
Despite these systemic issues, public policy has largely focused on supply-side interventions, such as expanding vocational training and skill development programmes. While important, these have not been matched by commensurate attention to labour demand, especially from MSMEs and labour-intensive sectors. The disconnect between skilling outcomes and actual job absorption remains a major obstacle to employment generation. The result is a skills paradox—millions trained but few absorbed—highlighting a dynamic economy navigating a critical phase in its development journey.

Against this landscape, our report examines the contours of India's evolving labour market, focusing on the quality of employment, sectoral multiplier effects, the dynamics of occupational mobility, and the structural barriers to job creation. Drawing on nationally representative surveys and administrative data, we assess whether India's current growth path can deliver not just more jobs, but better, more secure, and more inclusive employment. As India moves toward the vision of *Viksit Bharat 2047* armed with demographic strength and expanding digital capabilities, the imperative is clearly to build a labour market that is future-ready—resilient, equitable, and capable of unlocking the full potential of its people.

1.2. Labour Demand Constraints

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

Figure 1.1: Workforce Participation Rates (WFPR) by per capita income and education



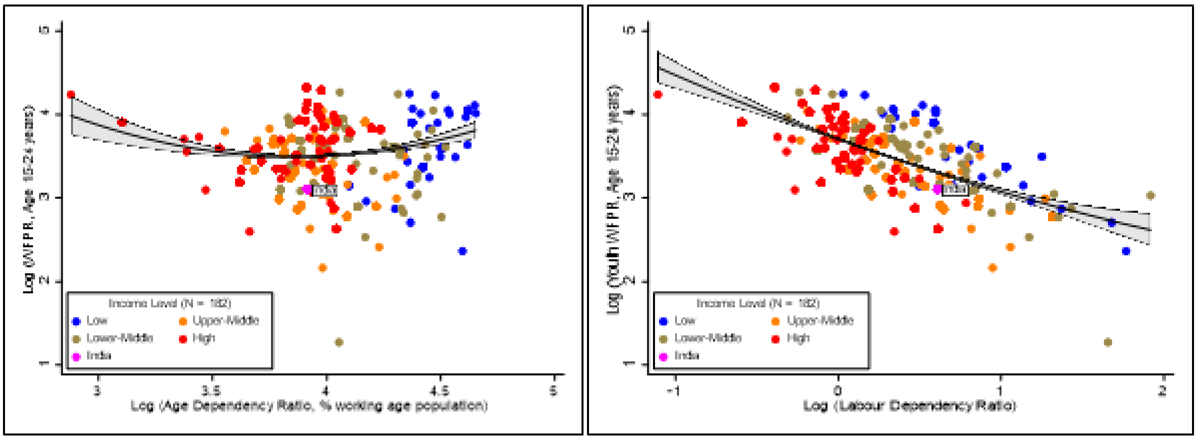
(a) WFPR vs per capita income (2018) **(b) WFPR vs Higher secondary education (2018)**

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

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

In addition, India, with its large youth population, has not been able to capitalise on the demographic dividend. The youth workforce participation in India is below the international trend line (Figure 1.2).

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



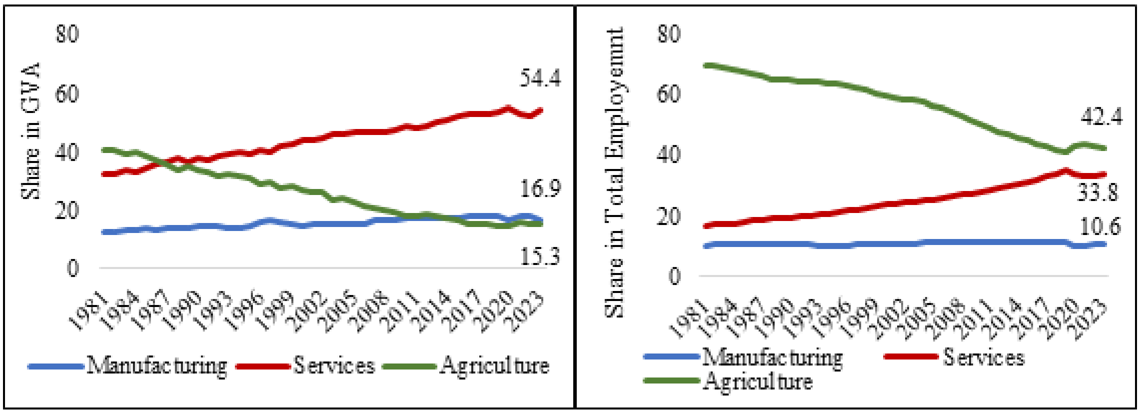
(a) Youth WFPR vs age dependency ratio (2018) **(b) Youth WFPR vs labour dependency ratio (2018)**

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

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

The *second* accompanying characteristic of India's labour force is its slow transformation, marked by an almost stagnant structure of labour force participation. Although the proportion of workforce employed in agriculture has declined, it still remains the largest at around 45 per cent. This is despite a significant fall in the contribution of agriculture to GDP (RBI KLEMS, 2024). The contribution of the manufacturing sector to employment has been mostly stagnant with most of the labour that has shifted away from agriculture being absorbed by the services sector (Figure 1.3). These trends stand contrary to the historical experience of developed countries, where the structural transformation of the economy progressed from agriculture to manufacturing before moving into services.

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

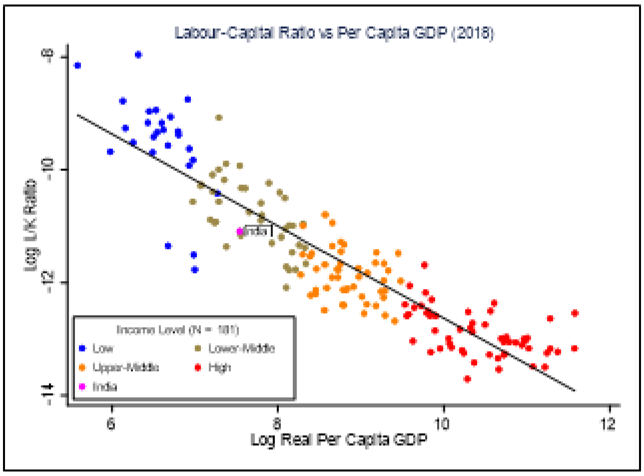


(a) **Sectoral share in total Gross Value Added** **(b) Sectoral share in total employment**

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

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

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

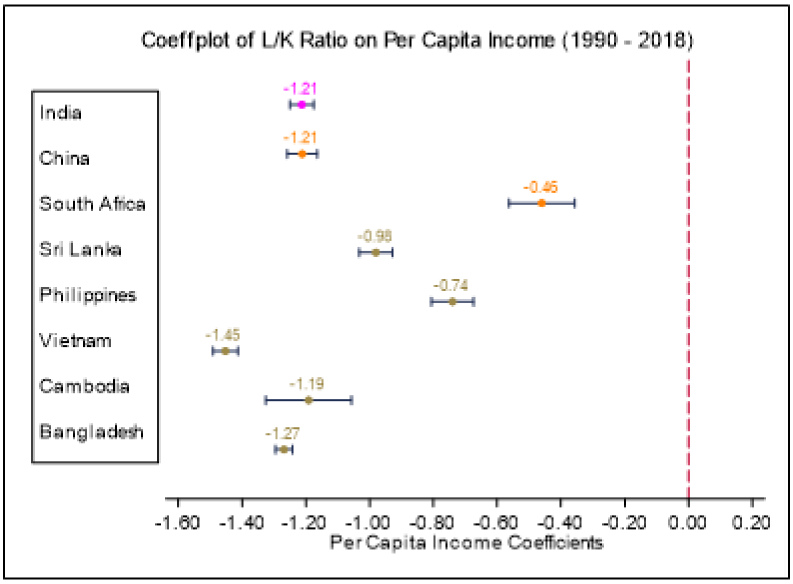


Source: Penn World Table (1990 -2018), Groningen Growth and Development Centre; World Bank database; Authors' calculations.

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

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

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



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

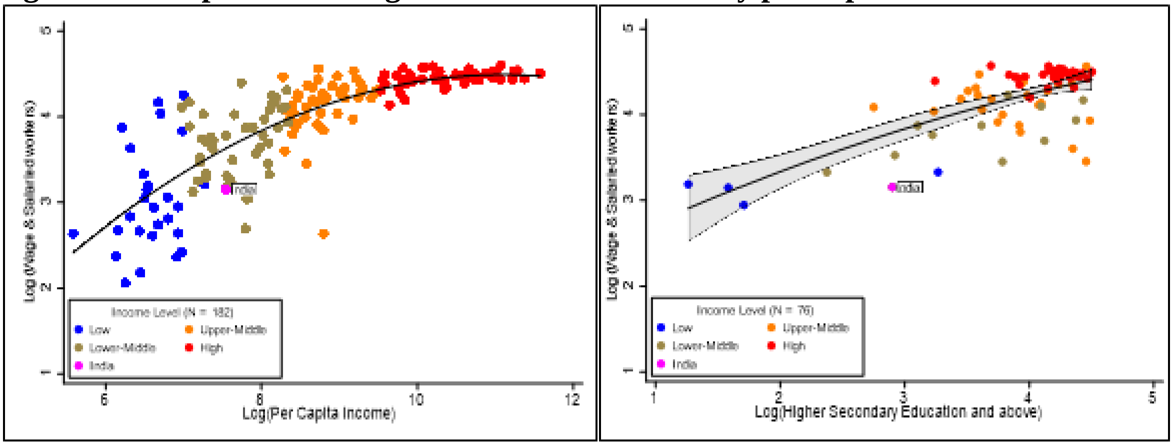
Note: i. L/K Ratio is the number of persons employed (in millions) divided by capital stock at constant 2017 USD prices; ii. Per Capita Income is in constant 2015 USD; iii. Both variables are taken in log form. The coefficients can be interpreted as percentage changes; iv. The colour scheme distinguishes the World Bank Income Groups with the countries arranged in decreasing order of Per Capita GDP (2018) after India; v. 95 per cent confidence interval bands.

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

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

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

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

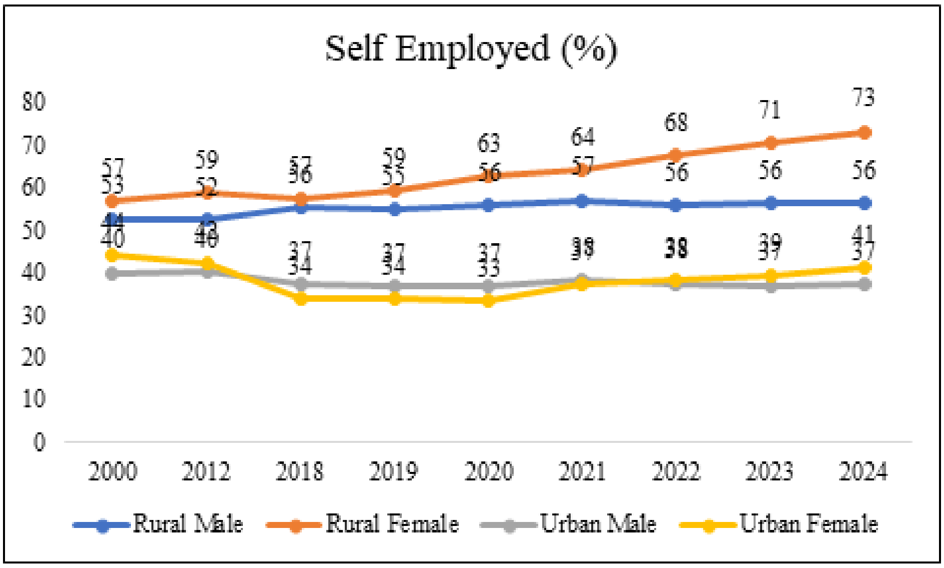


(a) Wage and salaried workers vs per capita income (2018) **(b) Wage and salaried workers versus higher secondary education (2018)**

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

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

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



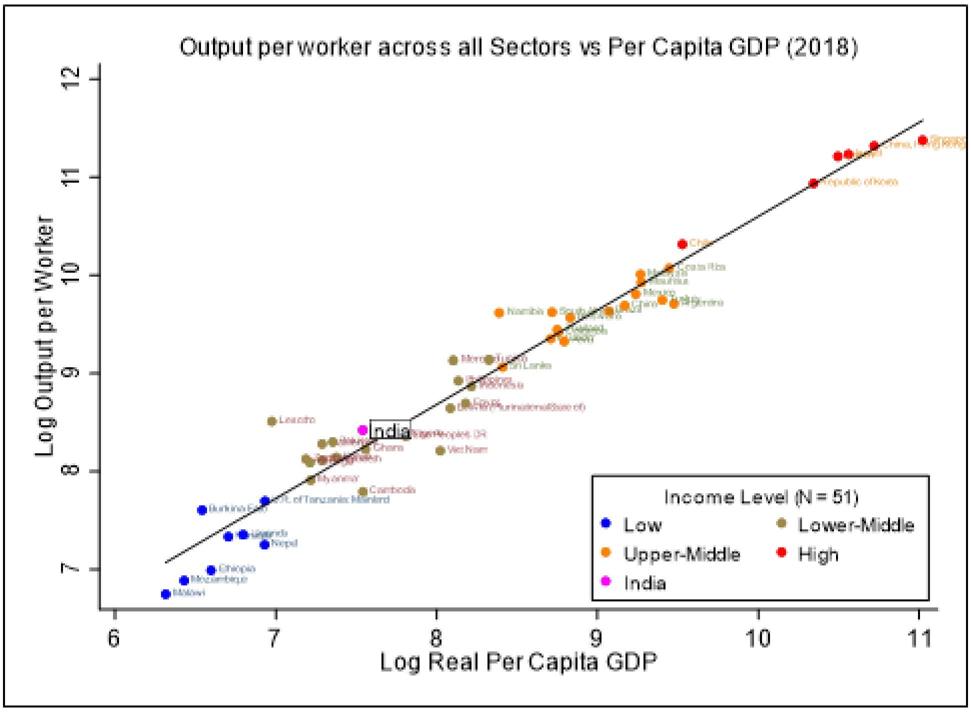
Source: Periodic Labour Force Survey (PLFS), 2017-18 to 2023-24; National Sample Survey 55th and 68th Rounds (NSS; 1999-200, 2011-12). Authors' calculations.
Note: i. Proportions are calculated as a percentage of total employment in each group; ii. The data spans the period from 1999-2000 to 2023-24, the latest year for which data is available; iii. Sample size is of 16.9 crore in 1999-2000 to 26.8 crore in 2023-24; iv. The NSS rounds are included to exhibit a longer trend.

1.3. Labour Supply Constraints

While Section 1.2 highlights the capacity constraints faced by the Indian economy in absorbing the labour force, we cannot ignore the prevalence of constrictions on the supply side of the labour market. The low level of human capital among India's working age population potentially restricts access to gainful and quality work opportunities. We empirically examine the cross-country relationship between labour productivity and real per capita income and India's position relative to other countries. We, therefore, analyse the global patterns of labour productivity against per capita income with a specific focus on India's performance over the last three decades.

Using the Economic Transformation Database (ETD) from the Groningen Growth and Development Centre, we calculate labour productivity (or output per worker) as the Gross Value Added (in constant USD, 2015) divided by the 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 1.8.

Figure 1.8: Labour productivity and per capita GDP



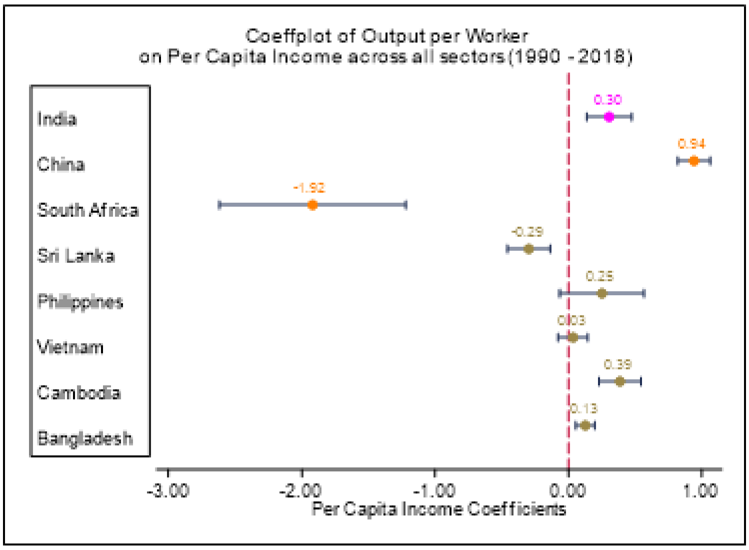
Source: Economic Transformation Database (ETD; 1990-2018), Groningen Growth and Development Centre; World Bank; Authors' calculations.

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

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

To assess the growth in labour productivity over time in India, we examine its relationship with real per capita income growth. Specifically, we regress the log of labour productivity for each country with the log of real per capita income over the period 1990-2018. 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 (regression models and results can be found in **Annexure A1**).

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

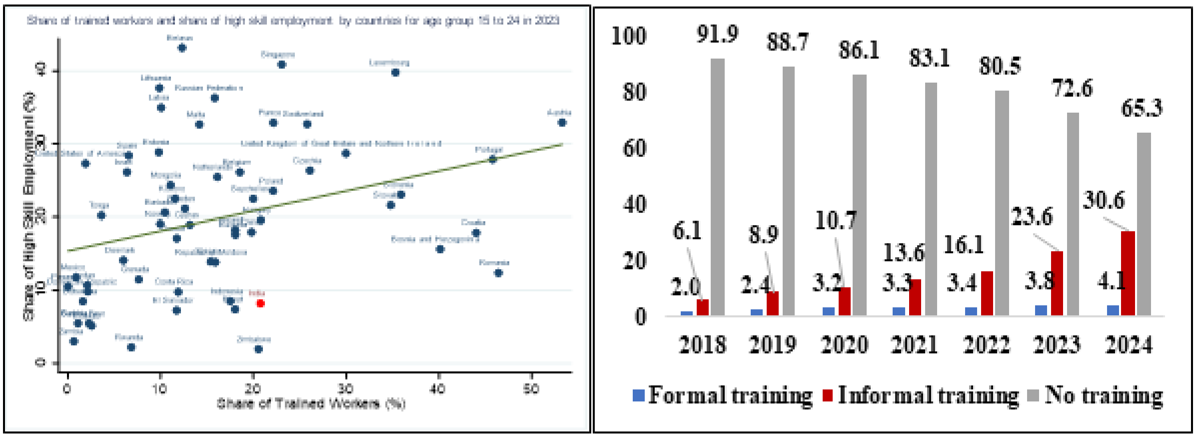


Source: Economic Transformation Database (1990-2018), Groningen Growth and Development Centre; World Bank; Authors' calculations.

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

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

Figure 1.10: High skill employment and trends in worker training



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

Source: ILOSTAT, International Labour Organization (2023); PLFS (2017-18 to 2023-24); Authors' calculations.

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

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

The analysis indicates that India needs to sharply increase the productivity of its labour 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 labour market (Acemoglu and Guerrieri, 2008). These dual constraints, viz., the limited supply of skilled labour and the economy's insufficient capacity to productively absorb the workforce, need to be urgently addressed. This study, therefore, aims to examine both dimensions to facilitate the creation of sustainable and inclusive employment opportunities in India.

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

In Chapter 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 labour-intensive sub-sectors, until 2030. In Chapter 3, we assess the potential impact of skill and vocational training on improving job opportunities in the manufacturing and services sectors between 2025 and 2030. Chapter 4 provides an analytical overview of the informal sector in India, highlighting critical areas for increasing the degree of formalisation in rural and urban employment. Chapter 5 presents the conclusion with policy implications.

Chapter 2
Loosening the Demand Constraints

2.1. Introduction

In this chapter, we consider three broad sectors: Agriculture and Allied Activities, Manufacturing, and Services.

Agriculture, Manufacturing, and Services together account for a significant share of the total GVA (around 86.7 per cent in 2023), with the following sectoral break-up:

- Agriculture: 15.35 per cent, Manufacturing: 16.92 per cent, and Services: 54.4 per cent

We follow the KLEMS classification to classify the sub-sectors into the Agriculture and Allied Activities, Manufacturing, and Services sectors.

- The Agriculture and Allied activities sector includes Agriculture, Hunting, Forestry, and Fishing.
- The Manufacturing sector comprises the following sub-sectors: Food Products, Beverages, and Tobacco, Textiles, Textile Products, Leather, and Footwear, Wood and Products of Wood, Pulp, Paper, Paper Products, Printing, and Publishing, Coke, Refined Petroleum Products, and Nuclear Fuel, Chemicals and Chemical Products, Rubber and Plastic Products, Other Non-Metallic Mineral Products, Basic Metals and Fabricated Metal Products, Machinery, not elsewhere classified (n.e.c), Electrical and Optical Equipment, Transport Equipment, Manufacturing n.e.c; Recycling.
- The services sector comprises the following sub-sectors: Trade, Hotels and Restaurants, Transport and Storage, Post and Telecommunication, Financial Intermediation, Business Services, Public Administration and Defence; Compulsory Social Security, Education, Health and Social Work, Other Services.

Mining and Quarrying, Electricity, Gas and Water supply and Construction are excluded from the three broad sectors mentioned above.

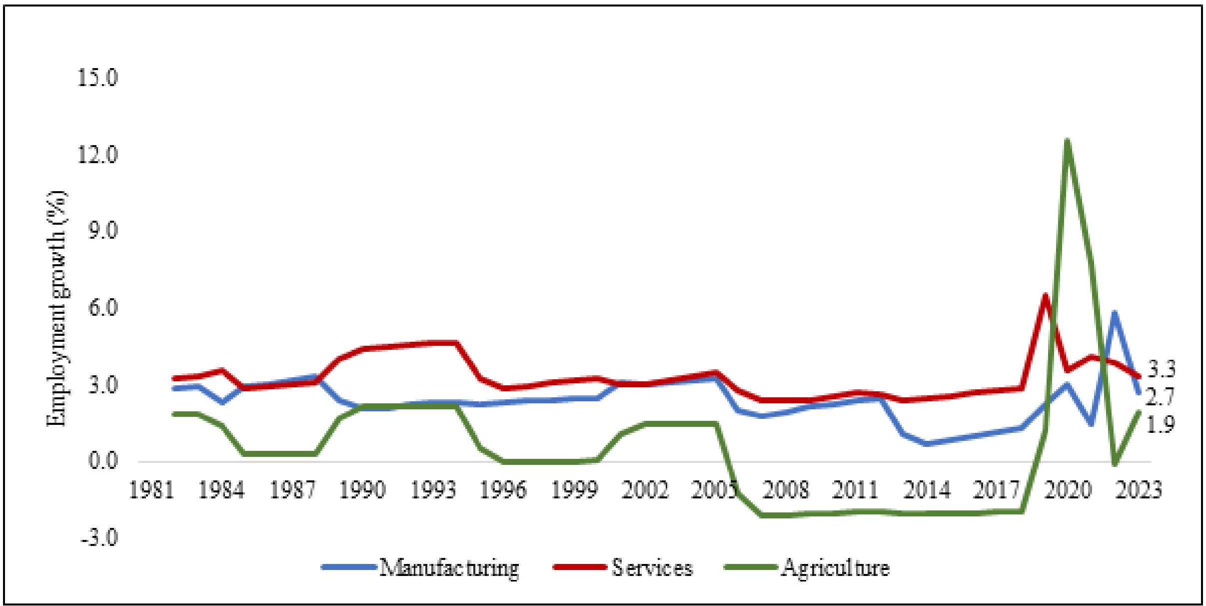
The Annual Survey of Industries (ASI) uses the financial year to define its reporting period. Similarly, the RBI KLEMS data relies on databases such as NAS and ASI, both of which use the financial year convention. Therefore, this study uses the financial year as the time period for analysis.

2.2. Trends in Employment Growth across Sectors (1981-2023)

This section presents an overview of employment growth across the agriculture, manufacturing, and services sectors, from 1981 to 2023, using the RBI KLEMS database. Between 1981 and 1991, all the three sectors experienced positive growth, with services leading at 3.50 per cent, followed by manufacturing (2.72 per cent), and agriculture (1.22 per cent). During the next decade (1991-2001), however, manufacturing growth decelerated to 2.42 per cent, while services growth accelerated marginally to 3.54 per cent. Employment growth in agriculture declined to 0.83 per cent. During the decade 2001-2011, manufacturing growth remained steady at 2.50 per cent. Growth in services decelerated to 2.83 per cent. The period 2012-2023 witnessed the highest volatility, specifically in agriculture. Employment growth in the services sector accelerated to 3.31 per cent, with employment growth in the manufacturing sector decelerating to 1.98 per cent. See Figure 2.1 and Table 2.1 for details.

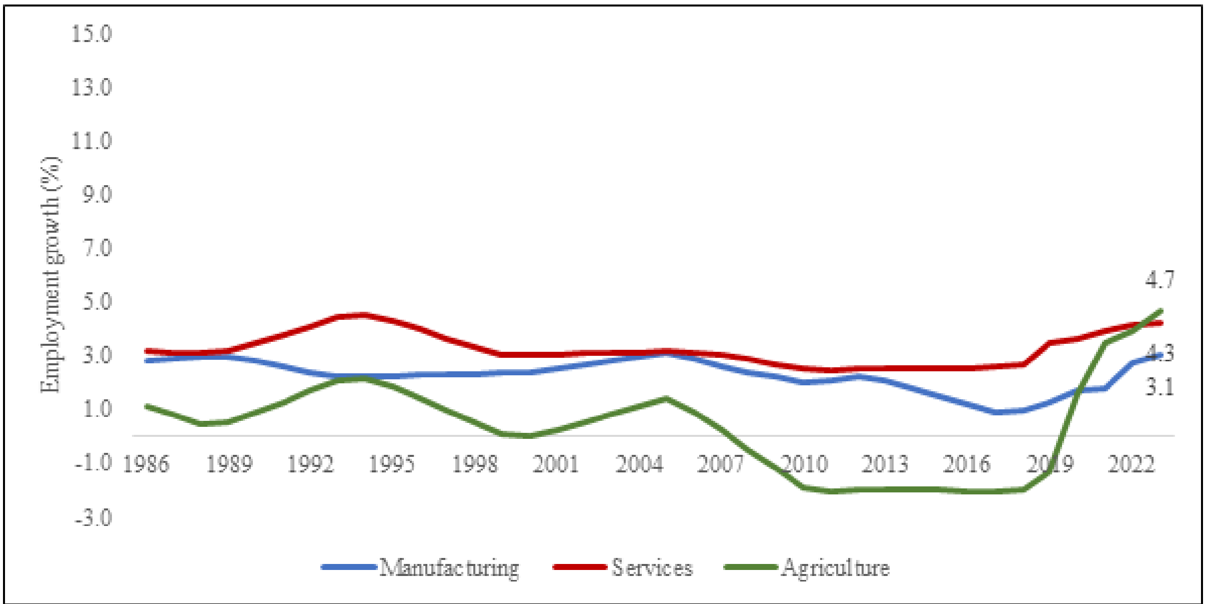
Overall, there was an insignificant increase in growth rates in employment between 1980 and 2022, with the pandemic shock leading to a reversal in the declining trend of agricultural employment.

Figure 2.1: Employment growth across sectors



Source: RBI KLEMS, 2024
Note: i. Employment growth in RBI KLEMS is computed using Tornqvist Aggregation. This method aggregates industry-level employment changes weighted by each industry's labour income. It accounts for the relative economic importance of labour inputs across industries ii. The data spans the period from 1981 to 2023, the latest year for which data is available.

Figure 2.2: Five-year moving average of employment growth across sectors



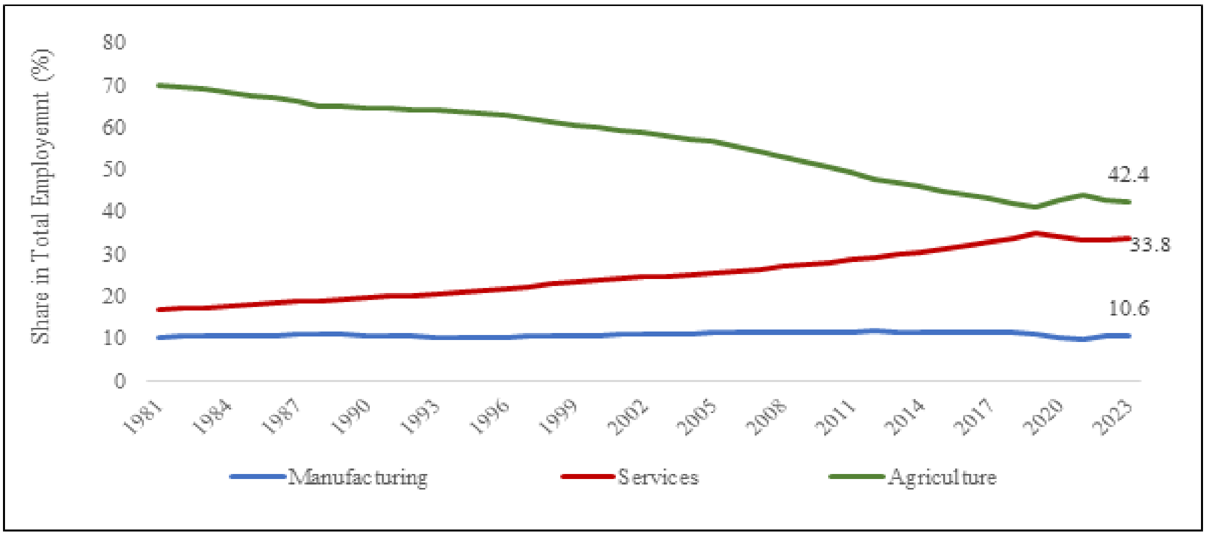
Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. The employment growth rate is calculated as a five-year moving average of the annual growth rates to smooth short-term fluctuations ii. Employment growth in RBI KLEMS is computed using Tornqvist Aggregation. This method aggregates industry-level employment changes weighted by each industry's labour income. It accounts for the relative economic importance of labour inputs across industries iii. The data spans the period from 1981 to 2023, the latest year for which data is available.

Table 2.1: Average employment growth

Sector	Year			
	1982 to 1990	*1991 to 2001*	*2002 to 2011*	*2012 to 2023*
Manufacturing	2.8	2.4	2.5	2.0
Services	3.4	3.6	2.8	3.3
Agriculture	1.1	0.9	-0.5	0.8

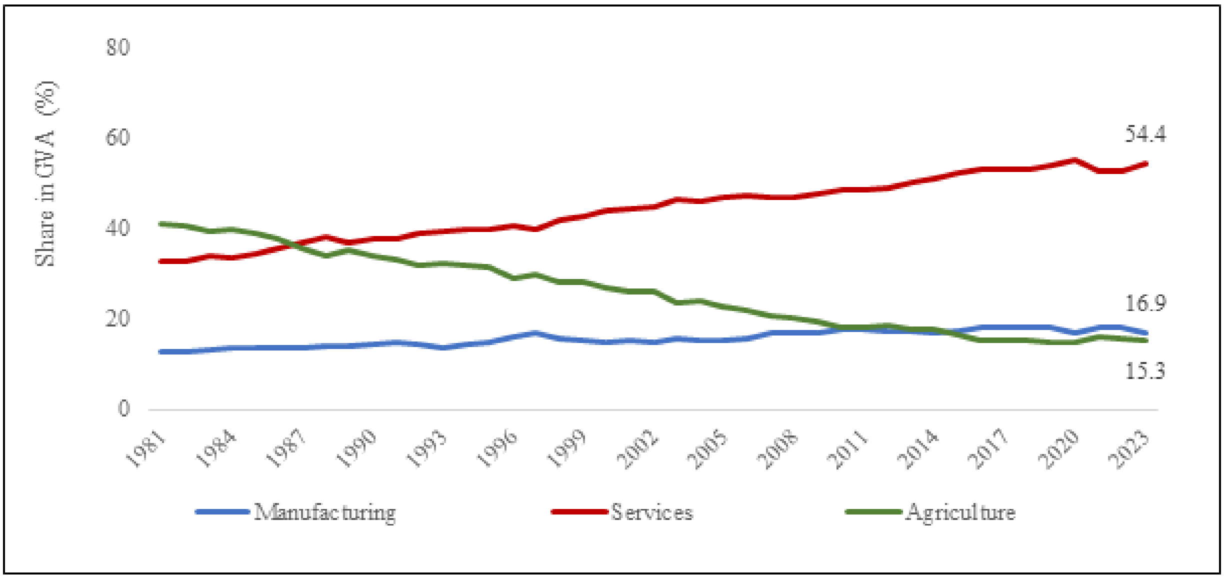
Source: RBI KLEMS, 2024; Authors' calculations.
Note: *i*. Employment growth in RBI KLEMS is computed using Tornqvist Aggregation. This method aggregates industry-level employment changes weighted by each industry's labour income. It accounts for the relative economic importance of labour inputs across industries ii. The data spans the period from 1981 to 2023, the latest year for which data is available.

Figure 2.3: Sectoral share in total employment



Source: RBI KLEMS, 2024; Authors' calculations.
Note: The data spans the period from 1981 to 2023, the latest year for which data is available.

Figure 2.4: Sectoral share in Gross Value Added (GVA)



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

2.3. Trends in the Labour Intensity of Production across Sectors (1981-2023)

2.3.1 Ratio of physical labour to physical capital

In this sub-section, we track the labour intensity of production from 1981 to 2023 for the manufacturing, services, and agricultural sectors.

We define labour intensity[1] as the ratio of Number of Persons Employed (in '000s) and Capital Stock at Constant 2011-12 Prices (Rs crore). The Capital to Labour (K/L) ratio has been used in literature to understand trends in capital intensity across sectors (Hassan et al., 2013; Kapoor, 2014). Considering that the focus of this study is on identifying the labour-intensive sectors, we use the Labour to Capital (L/K) ratio for the analysis. In the Indian context, the ASI data has been used predominantly to compute capital intensity (Kumar, 2021). The advantage of this study is that since we are using the RBI KLEMS database, we incorporate both formal and informal enterprises.

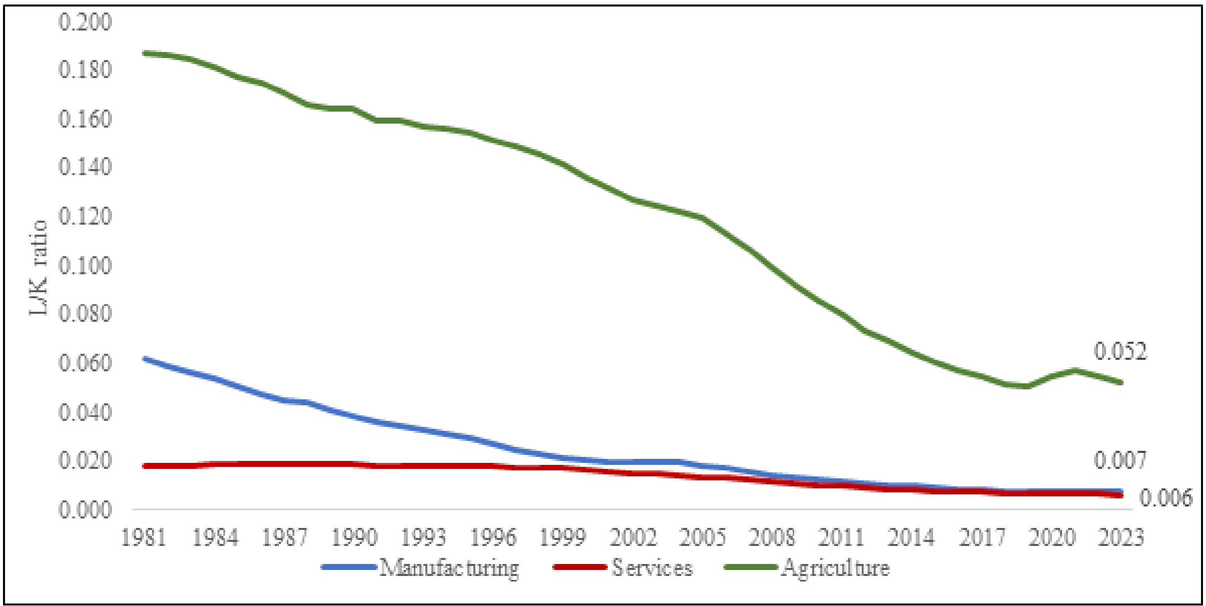
The L/K ratio measures the relative dependence on labour as compared to capital. A high L/K ratio implies that more labour is used per unit of capital. This is indicative of labour-intensive production. A low L/K ratio means that more capital is used per unit of labour. We classify sub-sectors as labour-intensive using the L/K ratio since it reflects the use of physical input quantities rather than input costs. Measures such as labour income as a share of value added may be influenced by real wages. Since our objective is to identify sectors that absorb more units of labour, the L/K ratio is a more appropriate measure.

The clear decline in the L/K ratio across sectors, over the years, is indicative of capital deepening, as shown in Figure 2.5. Interestingly, the L/K ratio of the services sector is lower than that of the manufacturing sector. While the number of 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 the L/K ratio in the services sector seems to have occurred at a faster pace post 2002.

Labour intensity within the traditionally labour-intensive[2] sub-sectors of both the manufacturing and services sectors (Table A2.4, Annexure A2) has declined considerably over the years. The capital intensive sub-sectors of the manufacturing and services sectors exhibit a modest decline in labour intensity. In the manufacturing sector, sub-sectors such as textiles and food products exhibit high labour intensity with relatively higher contribution to GVA (Table A2.1, Annexure A2). In the services sector, sub-sectors such as trade, business services, education, and health combine substantial GVA shares with high labour intensity and can be positioned as key engines of employment growth (Table A2.2, Annexure A2).

[1] The median labour to capital ratio for the manufacturing sector is 0.006 and is 0.009 for Services sector. The sub-sectors with values equal to and above median of the manufacturing sector are classified as labour intensive. Similarly, sub-sectors with values equal to and above median of the manufacturing sector are classified as labour intensive.

Figure 2.5: Labour to Capital (L/K) ratio by sector

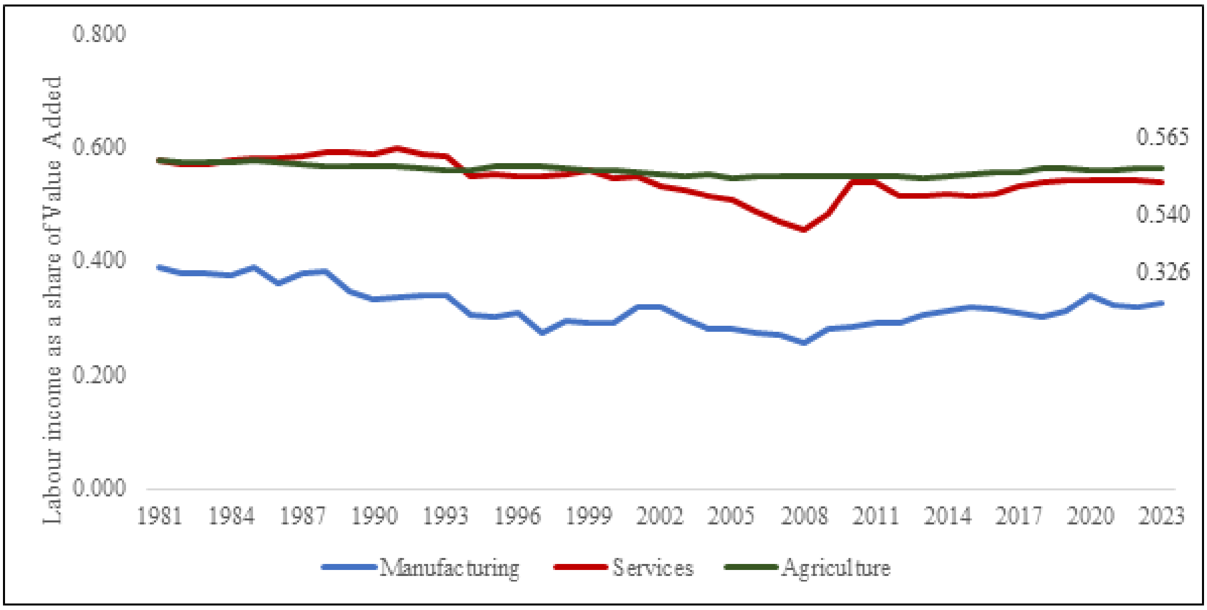


Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. L refers to Number of persons employed (in '000s) and K is the Capital stock in constant (2011-12) prices (Rs crores); ii. The labour to capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through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

2.3.2 Share of labour income in GVA

In addition to the physical definition of labour intensity, we also take into account labour income as a share of Gross Value Added.

Figure 2.6: Labour income as a share of Value Added by sector



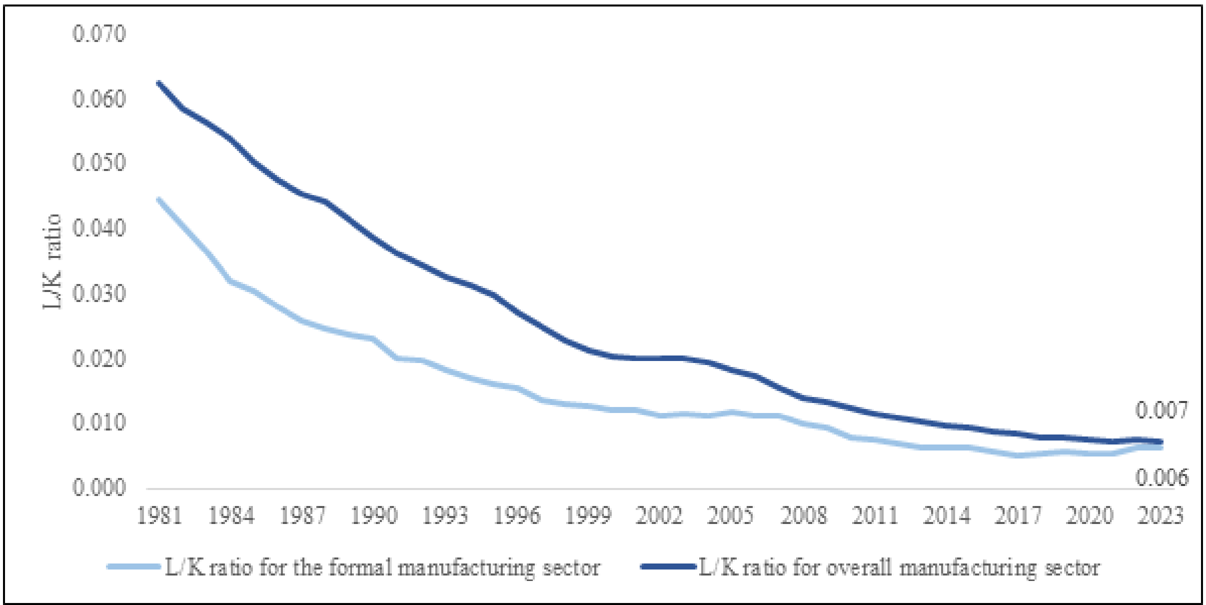
Source: RBI KLEMS, 2024
Note: i. In the RBI KLEMS dataset, labour income is estimated using NAS, ASI, and unit-level survey data of unorganized manufacturing enterprises. Compensation of Employees (CE), Operating Surplus (OS), and Mixed Income (MI) are derived for 27 study industries**:** ii. Gross Value Added (GVA) is in constant (2011-12) prices (Rs crores) iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data.

2.3.3 ASI database analysis

We also compute labour intensity using the ASI database. Here, we define labour intensity as the ratio of the 'Number of Persons Engaged' to the 'Real Fixed Capital' (Kumar, 2021; Kapoor, 2014). While the fixed capital series from ASI is in current prices, we have deflated it using the WPI manufacturing index. Real fixed capital is in constant 2011-12 prices.

We rank the more labour-intensive sub-sectors within manufacturing and services, separately, using the KLEMS database. We then focus on the sub-sectors with median or above labour intensity in the subsequent sections. The decline in L/K ratios has been sharp in the more labour-intensive sub-sectors in both manufacturing and services (see Annexure Figures).

Figure 2.7: Labour intensity in the formal manufacturing sector



Source: RBI KLEMS, 2024, Annual Survey of Industries (ASI)
Note: i. L refers to Total persons engaged (in '000s) and K is the Real Fixed Capital 2011-12 prices (Rs. crores) for the formal manufacturing sector; ii. The variable 'Fixed capital' has been deflated using the Wholesale Price Index (WPI) manufacturing index iii. The labour to capital (L/K) ratio represents labour intensity of a sector; iv. The dataset covers the period from 1981 through 2023

2.4. Trends in Employment Elasticity across Sectors

Employment elasticity measures the percentage change in employment as a result of one percentage point change in economic growth. It is indicative of an economy's ability to generate employment as a percentage of the growth. In essence, it summarises the sensitivity of employment to output growth.

Below we show the overall employment elasticity by sector. We then break down the employment elasticity for the most labour-intensive sectors in manufacturing and services (Table A2.10, Annexure A2), separately.[2]

[2] The methodology is detailed in section A2.6 of the Annexure.

2.4.1 Estimations – Formal Manufacturing Sector

Table 2.2 shows that employment elasticity has declined in the manufacturing sector and across many labour-intensive sub-sectors for three decades corresponding to the data delineated in Table 2.1. On the other hand, employment elasticity has increased across the services sub-sectors with high labour intensity (Table B2.2).

Table 2.2: Employment elasticity across sectors

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

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

The manufacturing sector showed a significant change between the 1980s and 2010s. However, the elasticity values for the agriculture and services are not significantly different in 2010s from the corresponding levels in the 1980s (Table A2.9, Annexure A2).

Table 2.3: Employment elasticity estimations in formal manufacturing sector based on CAGR methodology

Sector		**Year**			
		1981 to 1990	***1991 to 2001***	***2002 to 2011***	***2012 to 2023***
Manufacturing	CAGR	0.064	-0.082	0.433	0.596
	Log-log	0.015 (0.046)	0.184 (0.115)	0.470*** (0.031)	0.614*** (0.066)

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

2.5. Employment Multiplier

2.5.1. Overview

Employment multipliers quantify how changes in output or employment within a specific industry influence broader job shifts across the economy. They highlight an industry's significance in regional job creation, with a higher multiplier indicating a greater number of additional jobs generated. Every industry is connected to other economic sectors through backward linkages, which involve suppliers providing necessary materials, and forward linkages, where workers spend their earnings.

Beyond the direct employment an industry sustains, it also supports numerous indirect jobs. When industries with strong linkages experience job or output fluctuations, the effects ripple across multiple sectors. Backward linkages measure the demand a sector places on the suppliers of inputs and are, therefore, crucial for estimating the indirect effects of final demand shocks. These effects are captured through the Leontief inverse matrix, which reflects the propagation of final demand across sectors through backward linkages.

Indirect employment, or employment multipliers, stem from three key factors: supplier effects, re-spending effects, and government employment effects. Supplier effects refer to the impact that job creation or loss in one industry has on its suppliers (Bivens, 2019; Bhandhari et al., 2022).[3]

2.5.2. Estimations – Sector and Sub-sectors

Table 2.4: Employment multiplier estimations for labour-intensive sub-sectors

Sector	Backward linkage employment multiplier	No. of persons per Rs.1 crore GVO (at current prices)
	Manufacturing	
Textile 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 table 2018-19; RBI KLEMS, 2024; Authors' calculations.
Note: i. We estimate employment multiplier for the sub-sectors using the I-O tables for the year 2018-19; ii. The variables used to estimate the employment multiplier are all in current prices, i.e. Gross Value of Output (GVO) and Intermediate inputs; iii. The number of persons employed is from RBI KLEMS database.

2.6. Simulations

2.6.1. GVA growth for given elasticity for aggregate sectors

In this simulation, we induce varying scenarios of growth in the Gross Value Added, keeping the employment elasticity constant. We estimate the employment elasticity from KLEMS for the period 2012-2023 and keep it fixed for the simulations.

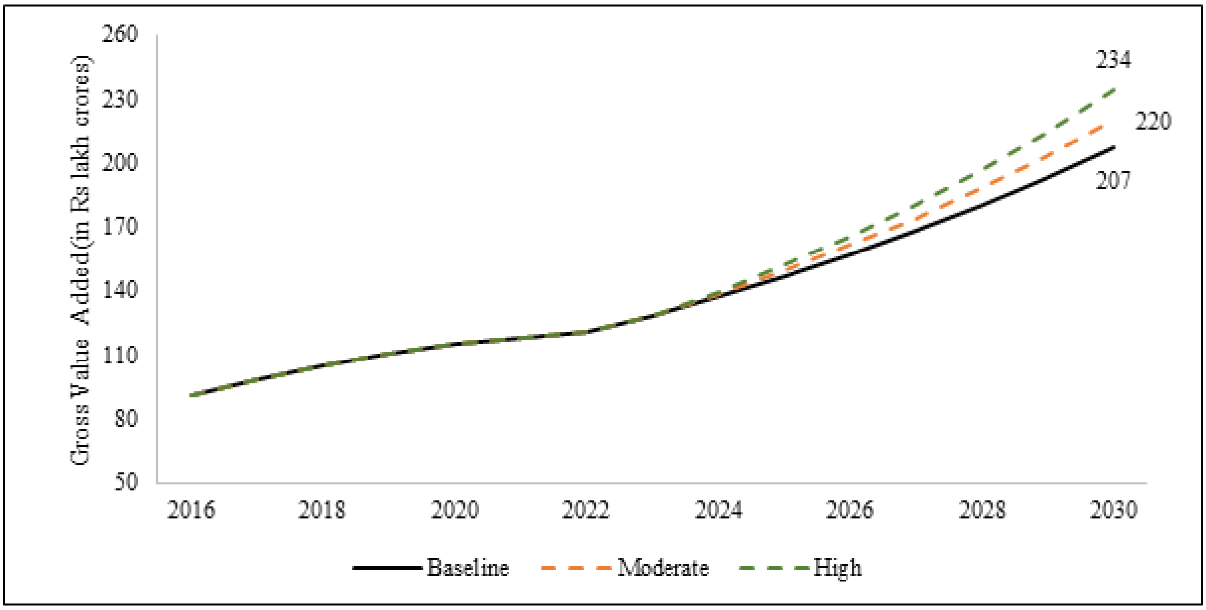
[3] The methodology is detailed in the Appendix (Section A7).

We have three scenarios for the growth in the GVA:[4]

- *Baseline growth scenario*: The average growth rate[5] for the sample period has been used to forecast GVA values for the period 2025-2030.
- *Moderate growth scenario*: GVA growth rate in the moderate growth scenario includes an addition of 0.5 of the standard deviation of average GVA growth rate. The GVA values are forecasted for the period 2025-2030 using this modified GVA growth rate.
- *High growth scenario*: GVA growth rate in the high growth scenario includes an addition of 1 of the standard deviation of the average GVA growth rate. The GVA values are forecasted for the period 2025-2030 using this modified GVA growth rate.

To estimate projected growth rates of GVA, we assume that sectoral shares of GVA are constant and that the GVA of agriculture grows at the 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 for estimating the growth rate of each GVA series (Figure 2.8). Since the agriculture, manufacturing, and services sectors together account for a significant share of total GVA (around 86.7 per cent in 2023; Agriculture: 15.35 per cent, Manufacturing: 16.92 per cent and Services: 54.4 per cent), 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 per cent GDP growth rate, with a focus on the period up to 2030 (Table 2.4).

Figure 2.8: Total GVA projections



Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. GVA values are in constant 2011-12 prices (Rs crores). 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.

[4] The year 2020-21 has been dropped when estimating the average growth rate for the period under consideration.
[5] The growth rate is estimated from 2012-13 to 2022-23.

Table 2.5: Total GVA growth rate (%)

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

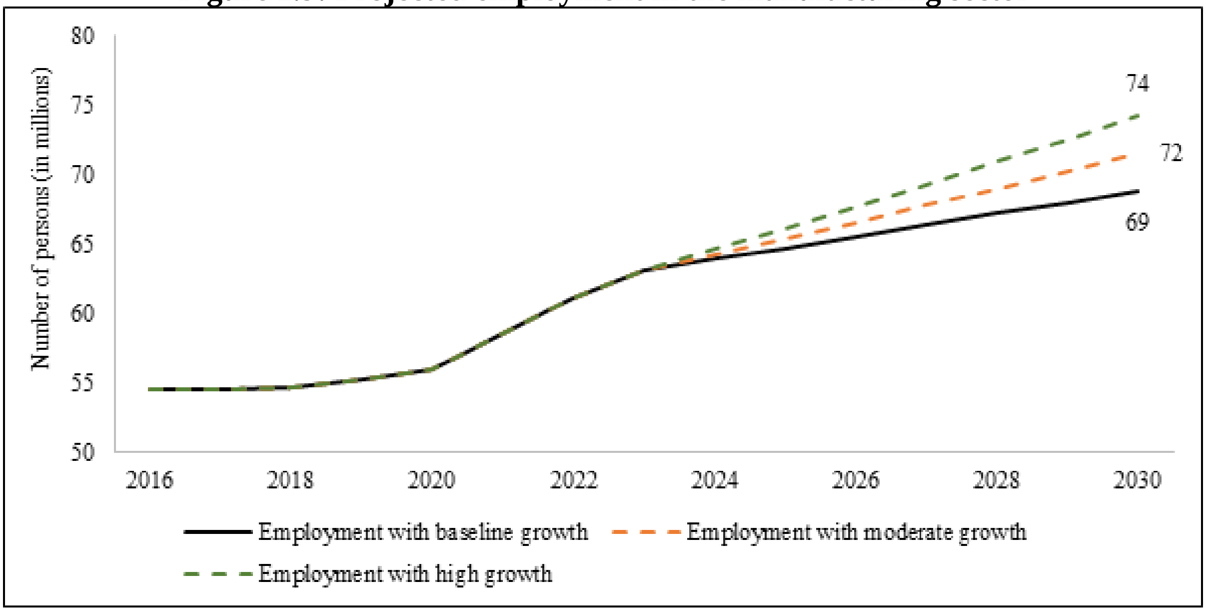
Source: Authors' calculations.
Note: GVA values are in constant (2011-12) prices (Rs. crores)

Our estimates indicate that if the manufacturing and services sectors grow at 8.2 per cent and 9.0 per cent, respectively, overall, a GVA annual growth of 8 per cent can be achieved. This represents the *moderate growth scenario*, where 0.5 standard deviation is added to the average growth rate for the period 2012-2023. GVA can grow at a higher growth rate, i.e., around 9 per cent, if the manufacturing sector grows at 10.7 per cent, and the services sector at 9.6 per cent. This is considered the *high growth scenario*, where a one standard deviation 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 a GVA growth of 8 per cent could lead to significant employment generation across sectors, as shown in the following sections.[6]

A. Manufacturing sector simulations

Figure 2.9: Projected employment in the manufacturing sector



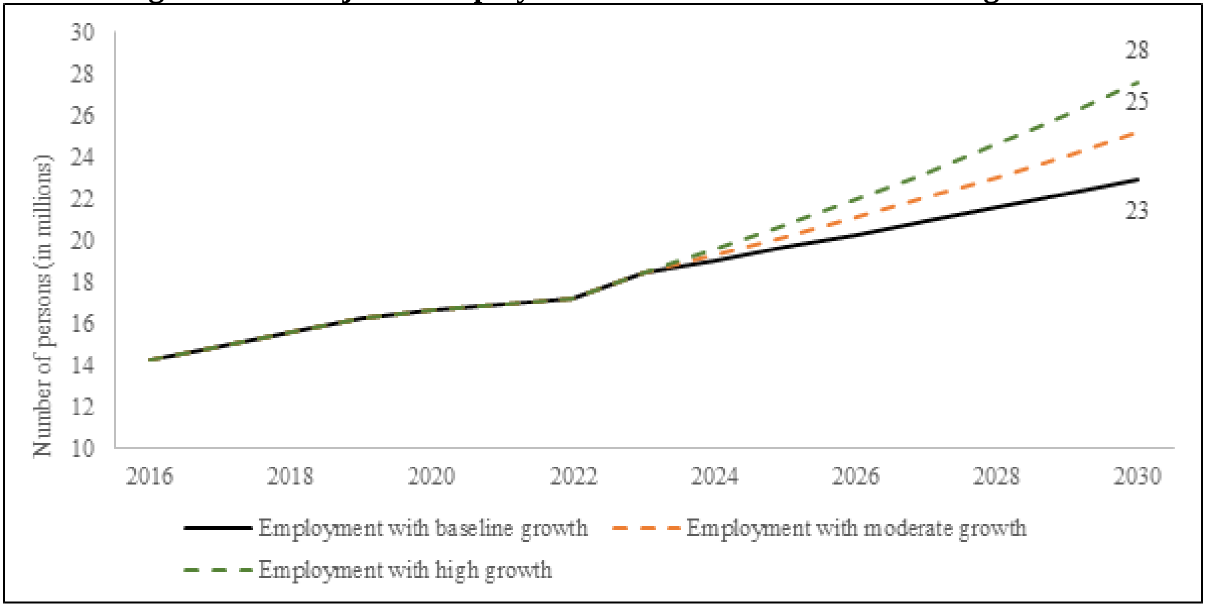
Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. Labour is defined as the number of persons employed (in millions) and the gross value added is in constant (2011-12) prices (Rs. crores); ii. The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic; iii.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

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

The Gross Value Added (at 2011-12 prices) of the total manufacturing sector, as of 2023, was Rs 25,04,663.330 crore. The GVA grew at 5.7 per cent, on an average, during the period 2012-2023. The GVA of the manufacturing sector will grow at 8.2 per cent in the moderate growth scenario, and at 10.7 per cent 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.

In the baseline growth scenario, the projected number of persons employed is 68,889,000. The projection for number of persons employed in the moderate growth scenario is 3.9 per cent higher than in the baseline scenario, at 71,544,000 persons. In the high growth scenario, it is 7.8 per cent higher than employment in the baseline scenario (Figure 2.9).

Figure 2.10: Projected employment in the formal manufacturing sector



Source: Annual Survey of Industries; Authors' calculations.
Note: i. Labour is defined as the total number of persons engaged (in millions) and the gross value added is in constant (2011-12) prices (Rs. crores) ii. The gross value added has been deflated using the WPI manufacturing index; iii The year 2020–21 is excluded from the analysis due to the adverse effects of the COVID-19 pandemic; iv. Data used to project GVA spans from 2012 to 2023.

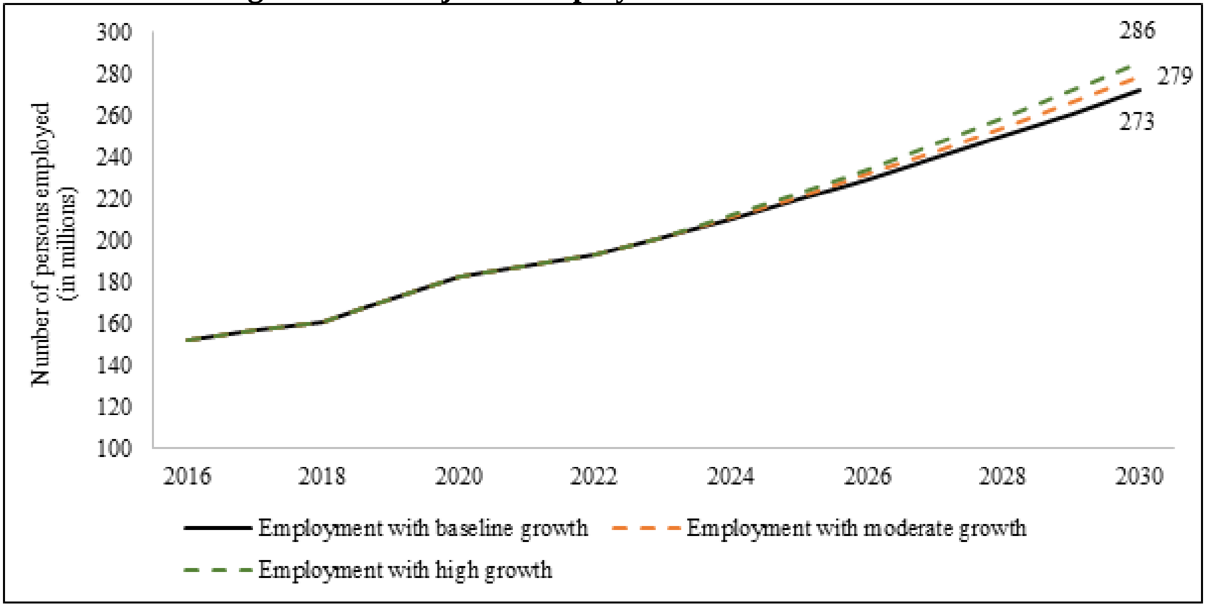
The formal manufacturing sector has been analysed using data from the Annual Survey of Industries (ASI). The projected number of persons employed in the year 2030 increases to 22,958 in the baseline scenario, to 25,181 persons, in the moderate growth scenario, and to 27,587 persons in the high growth scenario (Figure 2.10).

The Gross Value Added (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 per cent, on average, during the period 2011-12 to 2023. The GVA of the services sector will grow at 9.0 per cent in the moderate growth scenario, and at 9.6 per cent in the high growth scenario.

B. Service sector simulations

In Figure 2.11, we observe that in the services sector, 272,518,000 persons are projected to be employed by 2030 with the baseline GVA growth. The projected number of persons employed increases by 2.4 per cent to 2,79,130,000 with moderate GVA growth. It increases by 4.9 per cent to 285,880,000 with high GVA growth.

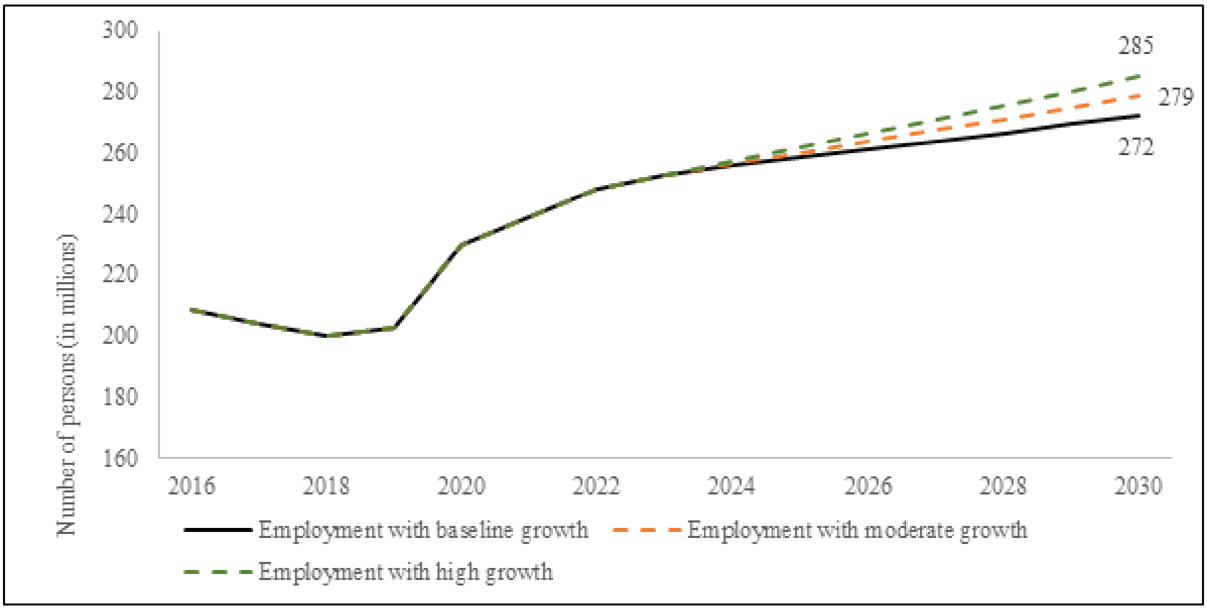
Figure 2.11: Projected employment in the services sector



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

The Gross Value Added (at constant 2011-12 prices) of the agriculture sector, as of 2023, is Rs 2,272,250.475 crore. The GVA grew at 3.8 per cent, on average, during the period 2012- 2023. The GVA of the agriculture sector will grow at 5.2 per cent in the moderate growth scenario, and at 6.5 per cent in the high growth scenario.

Figure 2.12: Projected employment in the agriculture sector



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

In Figure 2.12, we observe that in the agriculture sector, 272,161 persons are projected to be employed by 2030 with the baseline GVA growth. The projected number of persons employed increases by 2.5 per cent to 278,926 with moderate GVA growth, and by 5 per cent to 285,835 with high GVA growth.

Table 2.9: Projected employment with moderate and high GVA growth

Year	Manufacturing		Services		Agriculture	
	Employment with moderate GVA growth	Employment with high GVA growth	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	260	262
2026	67	68	232	234	264	267
2027	68	69	243	246	268	271
2028	69	71	254	259	271	276
2029	70	73	266	272	275	281
2030	72	74	279	286	279	286

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

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

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

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

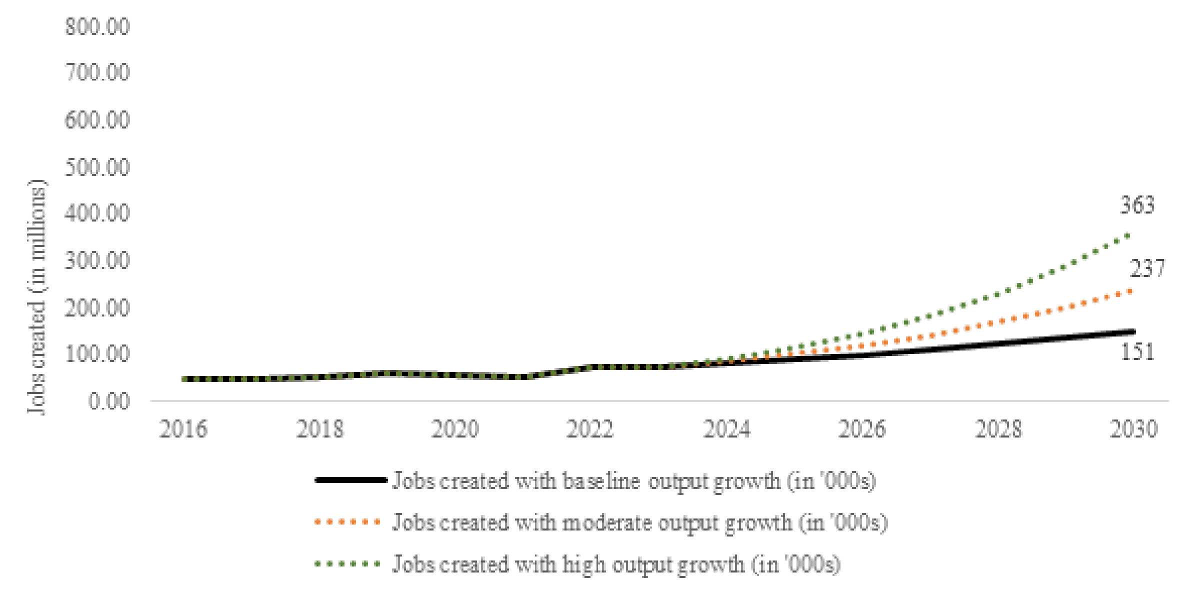
The employment multiplier is multiplied with the GO for the three scenarios to arrive at the aggregate number of jobs created for each scenario from the expansion of each labour-intensive sub-sector.[7].

A. Manufacturing labour intensive sub-sectors

The GO for textiles as of 2023 is Rs 1,534,041 crores. The gross output grew at 11 per cent, on average, from 2012 to 2023. This growth rate has been considered for constructing the baseline scenario. The GO is expected to grow at 18.5 per cent in the moderate growth scenario, and at 25.9 per cent in the high growth scenario.

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

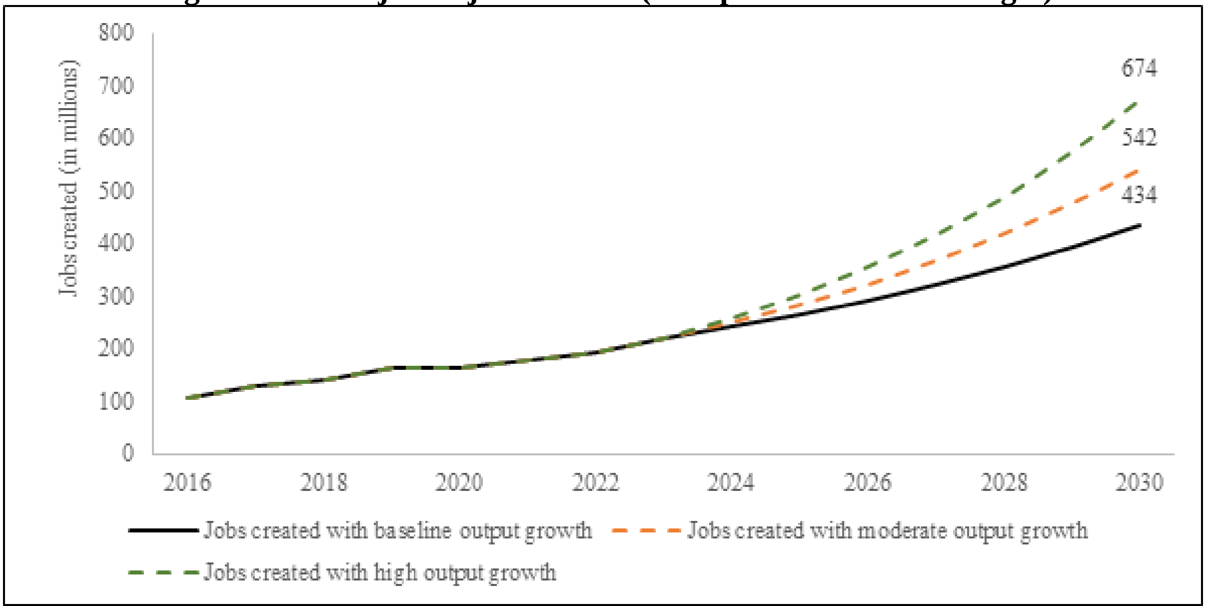
Figure 2.13: Projected job creation (textile and textile products)



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

In the baseline scenario, the GO grows at the rate of the average growth rate for the period 2012- 2023. As a result, the number of jobs created in the textiles and textile products industry is projected at 150,704 for the year 2030 (Figure 2.13). The projected number of jobs created in the moderate and high growth scenarios are 57 per cent and 140 per cent, respectively, which are higher than in the baseline growth scenario.

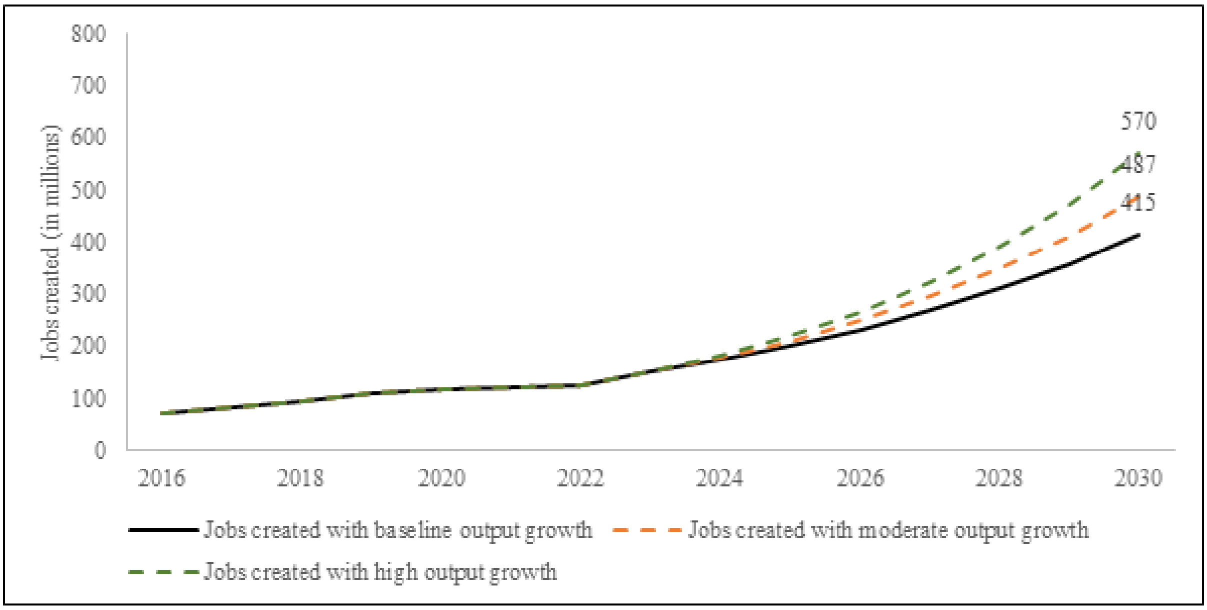
Figure 2.14: Projected job creation (food products and beverages)



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

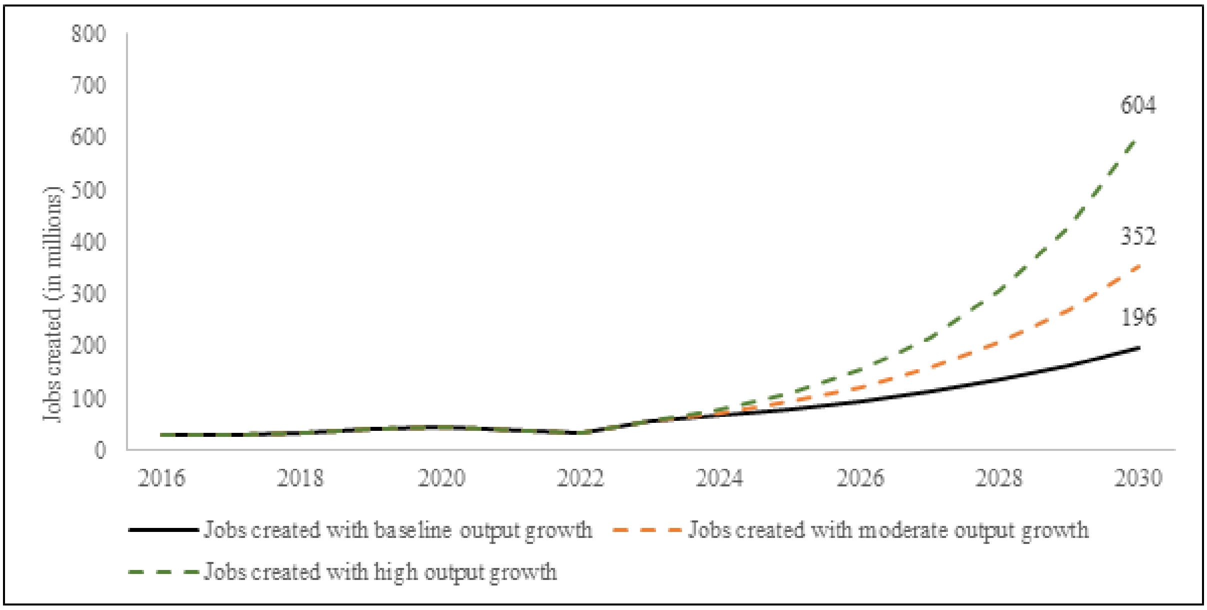
B. Services labour-intensive sub-sectors

Figure 2.15: Projected job creation (trade)



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

Figure 2.16: Projected job creation (hotels and restaurants)



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

Box B2.1: Formal Manufacturing

Interestingly, employment elasticity in formal manufacturing has been increasing unlike in the entire manufacturing sector. This pattern is evident for various sub-sectors, such as food products and beverages, where the elasticity has declined as part of the overall manufacturing sector but has increased in the formal manufacturing sector, between 1981 and 2023. The labour-intensive sub-sectors such as textiles and food products show declining or negative elasticity in the overall manufacturing sector, whereas the same sectors exhibit increases in elasticity in the formal segment. These patterns suggest a structural transformation in Indian manufacturing, with formal firms becoming more labour-intensive even as overall manufacturing is becoming less labour-intensive. This indicates that the observed decline in employment elasticity is driven by the informal manufacturing sector.

Table B2.1: Employment elasticity estimations in formal manufacturing sector based on CAGR methodology

Sector		Year			
		1981 to 1990	*1991 to 2001*	*2002 to 2011*	*2012 to 2023*
Manufacturing	CAGR	0.064	-0.082	0.433	0.596
	Log-log	0.015 (0.046)	0.184 (0.115)	0.470*** (0.031)	0.614*** (0.066)

Source: Annual Survey of Industries (ASI) database; Authors' calculations.
Note: We estimate employment elasticity from 1980–81 to 2022–23. The sample period is divided into four broad time periods to illustrate the evolution of elasticity over time. Labour is defined as the number of persons employed (in '000s); iv. Gross Value Added is in constant prices (2011- 12) prices (Rs crores). 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 ***, ** and * for 1 per cent, 5 per cent, and 10 per cent levels, respectively.

Table B2.2: Employment elasticity in formal manufacturing sector using Log-Log regressions

Sector	Year			
	1981 to 1990	*1991 to 2001*	*2002 to 2011*	*2012 to 2023*
Formal manufacturing (total)	0.015 (0.046)	0.184 (0.115)	0.470*** (0.031)	0.614*** (0.066)
Textile and textile products	-0.122 (0.124)	0.337*** (0.079)	0.638*** (0.074)	0.480*** (0.064)
Food products, beverages and tobacco	-0.152 (0.091)	0.150*** (0.046)	0.193*** (0.012)	0.370*** (0.051)
Electrical and optical equipment	0.270*** (0.022)	0.199* (0.106)	0.618*** (0.069)	0.782*** (0.160)
Wood and wood products	-0.176 (0.104)	0.359 (0.233)	0.479*** (0.073)	0.401*** (0.057)
Cement and other non-metallic minerals	0.208*** (0.020)	-0.001 (0.052)	0.418*** (0.077)	0.290*** (0.083)
Pulp, paper, paper products, printing, and publishing	-0.073 (0.069)	0.095 (0.119)	0.564*** (0.056)	0.334*** (0.067)
Gems, jewellery and miscellaneous	0.000 (0.048)	0.414*** (0.045)	0.741*** (0.092)	0.876*** (0.084)

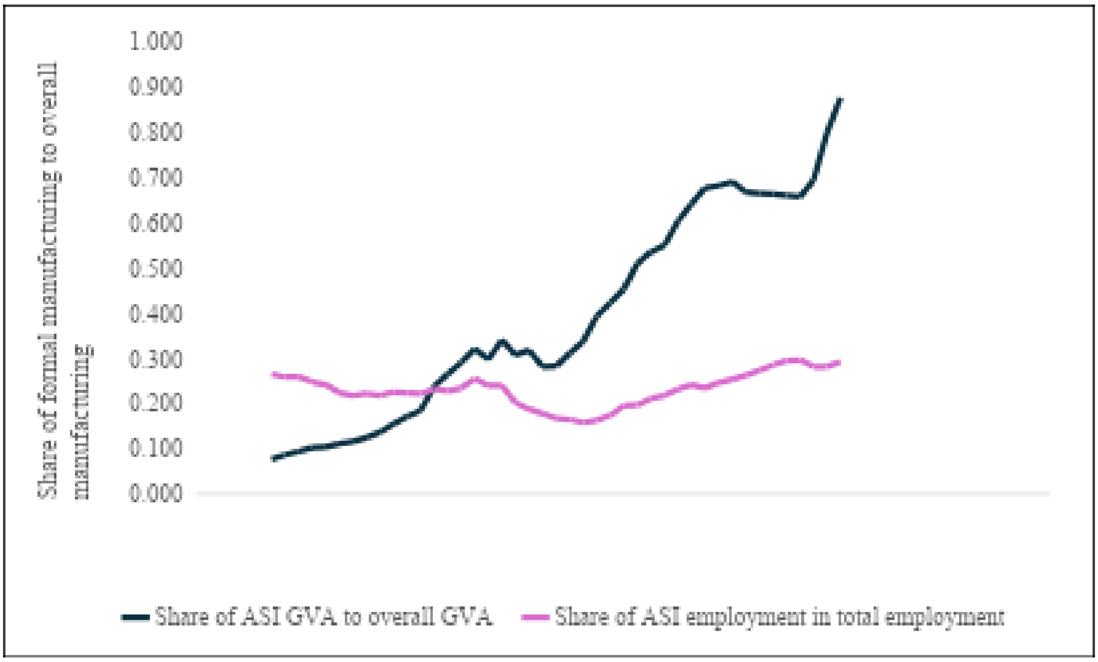
Source: Annual Survey of Industries (ASI) database; Authors' calculations.
Note: We estimate employment elasticity for the sub-sectors from 1980–81 to 2022–23. The sample period is divided into four broad time periods to illustrate the evolution of elasticity over time. Labour is defined as the

total number of persons engaged (in millions) and the gross value added is in constant (2011-12) prices (Rs crores). The Gross Value Added has been deflated using the WPI manufacturing index. 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 ***, ** and * for 1 per cent, 5 per cent, and 10 per cent levels, respectively.

Box B2.2: Why is elasticity in the informal sector declining and the elasticity in the formal sector increasing across decades?

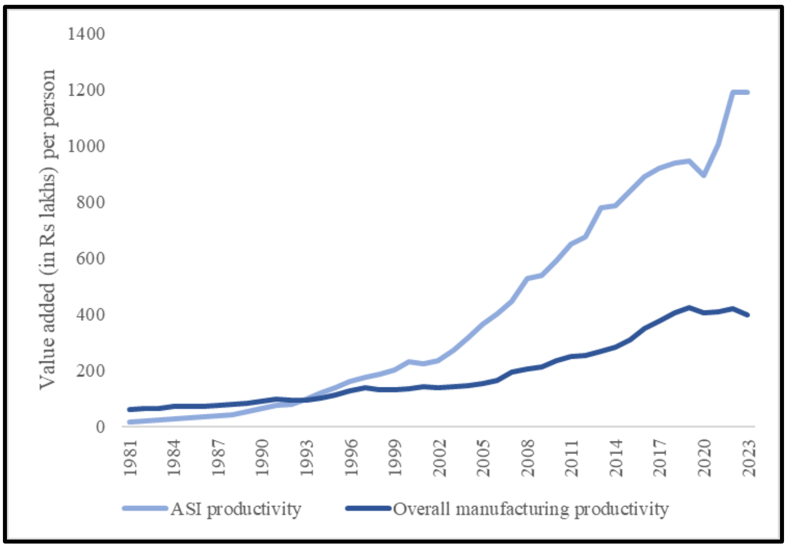
The contribution of formal sector manufacturing to total output has considerably increased over the years, especially post 2000. However, its share in employment remains somewhat stable (Figures B2.1 and B2.2). Thus, while the labour intensity in formal manufacturing and overall manufacturing has declined, the capacity of the formal sector to generate more units of output is higher than that of the overall manufacturing sector.

Figure B2.1: Share of labour and GVA of formal manufacturing in overall manufacturing



***Source*:** Annual Survey of Industries (ASI) database, RBI KLEMS 2024; Authors' calculations.
Note: For overall manufacturing, the data is sourced from RBI KLEMS, where GVA is in constant 2011-12 prices (Rs crores) and number of persons employed is in thousands. GVA from the ASI database has been deflated to constant 2011-12 prices (Rs crores) using the WPI manufacturing index. The total number of persons engaged (in '000s) from ASI is used as the labour input for the formal manufacturing sector.

Figure B2.2: Labour productivity in formal manufacturing and overall manufacturing

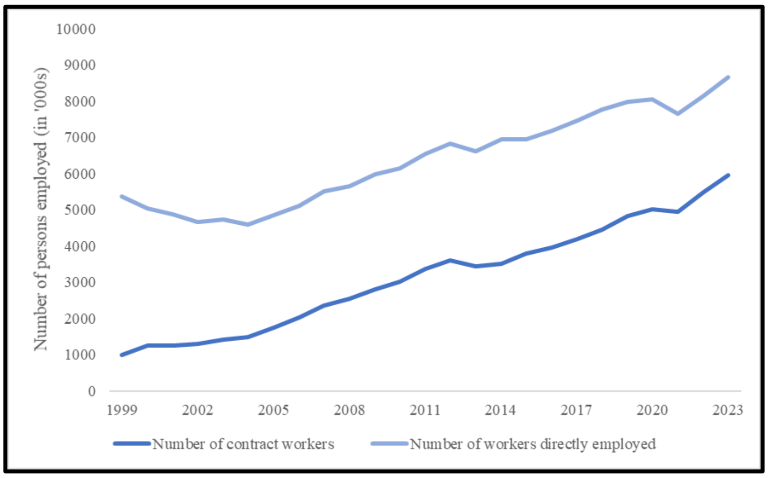


Source: Annual Survey of Industries (ASI) database, RBI KLEMS 2024; Authors' calculations.
Note: For overall manufacturing, the data is sourced from RBI KLEMS, where GVA is in constant 2011-12 prices (Rs crores) and number of persons employed is in thousands. GVA from the ASI database has been deflated to constant 2011-12 prices (Rs crores) using the WPI manufacturing index. The total number of persons engaged from GVA is used as the labour input for the formal manufacturing sector. Labour productivity is estimated as the Value Added (in Rs crores) per '000 persons employed.

On the one hand, the adoption of digital compliance measures, including *e-Shram* registrations, Goods and Services Tax (GST) systems, and real-time payroll monitoring, has likely encouraged firms to report more of their workforce, formalizing previously unregistered workers (Kapoor, 2019). However, a growing number of formal firms rely on casual, contractual, and third-party workers who lack access to basic employment rights and social protections. The India Wage Report published by the International Labour Organization *(ILO, 2018)* found that over 71 per cent of wage workers in formal enterprises were employed without written contracts or social security coverage. Supporting this, analyses of ASI data reveal that more than half of the workers in formal manufacturing firms are informally employed, with the trend intensifying in the post-2010 period (Mehrotra and Gandhi, 2019; Kapoor, 2019).

Conversely, the decline in overall manufacturing elasticity highlights the growing weakness of the informal sector, which has historically served as a critical source of labour absorption for low-skilled workers. This decline is driven by the cumulative effects of policy shocks, such as demonetisation, the GST rollout, and the COVID-19 pandemic, which disproportionately impacted micro and small enterprises. Many of these informal units either ceased operations or failed to recover, resulting in the concentration of output growth within capital-intensive formal firms that employ relatively fewer workers per unit of output. This has led to what the OECD (2019) describes as the "formalization of output without formalization of employment" (Abraham and Sasikumar, 2017; OECD, 2019).

Figure B2.3: Number of contract and directly employed workers



Source: Annual Survey of Industries (ASI) database; Authors' calculations.
Note: The average growth rate (1999-2023) in the number of contract workers is 7.95 per cent and that for directly employed workers is 2.09 per cent. Authors' calculations.

Chapter 3
Unleashing the Supply of Quality Labour

3.1. Overview of the Skilling Problem

The lack of skilling in India can be looked at from the demand and supply points of view. The focus on the demand side indicates which industries are generating employment. The supply side suggests whether there are enough adequately trained workers to meet this demand. The employment patterns in specific industries can be linked to the extent that there is a supply of trained labour force. In the subsequent sections, we explore which industries are driving job creation in India (on the demand side) and whether the supply of trained workers is sufficient to meet these emerging needs.

3.2. Demand for Skills

3.2.1. Skill Distribution for the Aggregate Economy

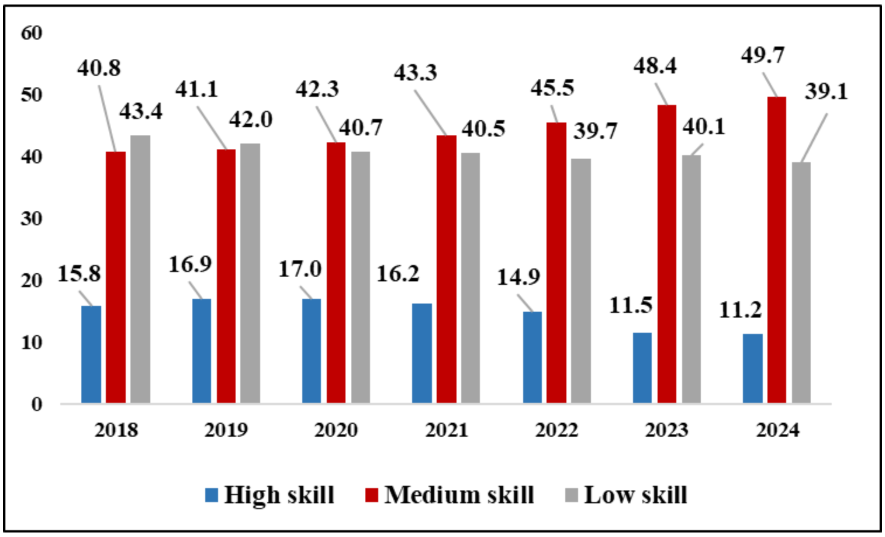
This section presents an overview of employment trends and growth at the aggregate economy level from 2018 to 2024, based on Periodic Labour Force Survey (PLFS) data. The detailed description of the PLFS data is given in Annexure A3.1.1.

Skill categorisation is based on the first-digit classification of National Classification of Occupations (NCO) codes (refer to Annexure A3.1, for details).

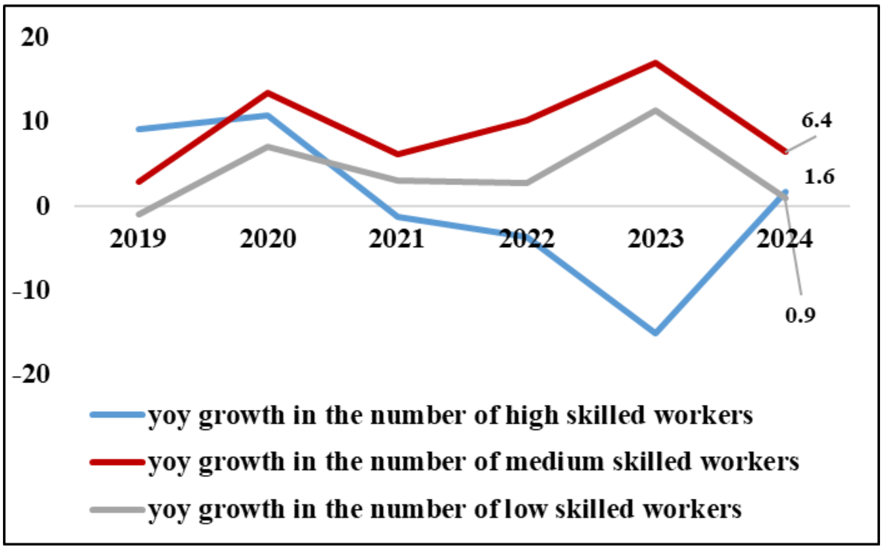
As shown in Figure 3.1, low-skill employment accounted for the largest share of total employment in 2018. Over time, the share of both low-skill and high-skill employment has declined, while the share of medium-skill employment has increased. The share of medium-skill employment rose from 40 per cent in 2018 to nearly 50 per cent in 2024, making it the largest contributor to total employment in that year.

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

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



a) Distribution of employment by skills



b) Y-o-Y growth in employment by skills

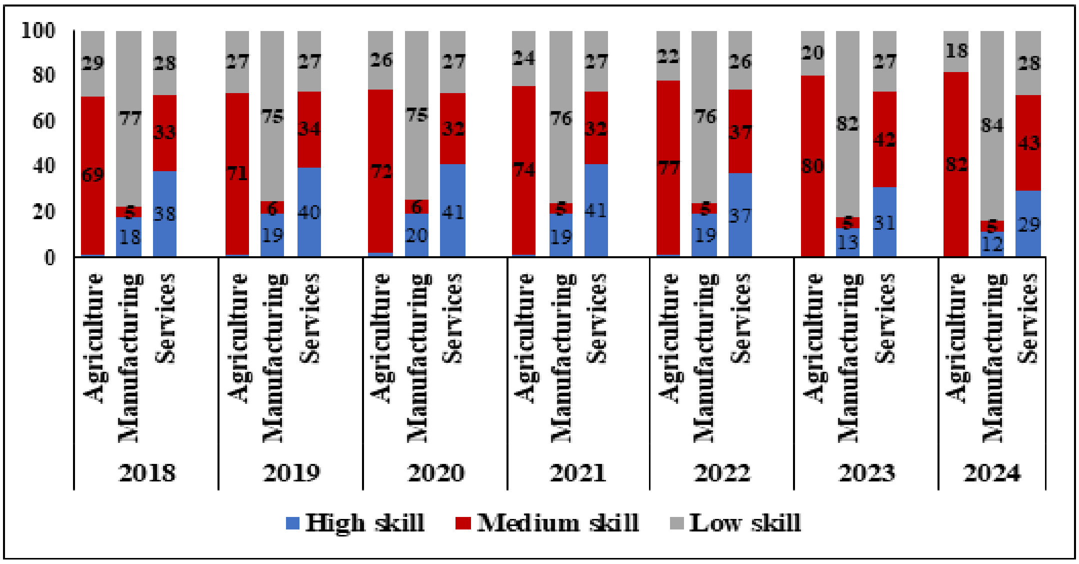
***Source**:* PLFS (2018 to 2024); Authors' calculations.
***Note**:* i. The agriculture sector includes 2-digit industry codes from 01 to 03; the manufacturing sector includes 2-digit industry codes from 10 to 33; and the services sector includes 2-digit industry codes from 45 to 99; ii. Skill categorisation is based on NCO (1-digit level). Weighted sample size varies from 341 million in 2018 to 475 million in 2024.

3.2.2. Skill distribution within Agriculture, Manufacturing, and Services

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

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

Figure 3.2: Employment distribution by skills within agriculture, manufacturing, and services (%)

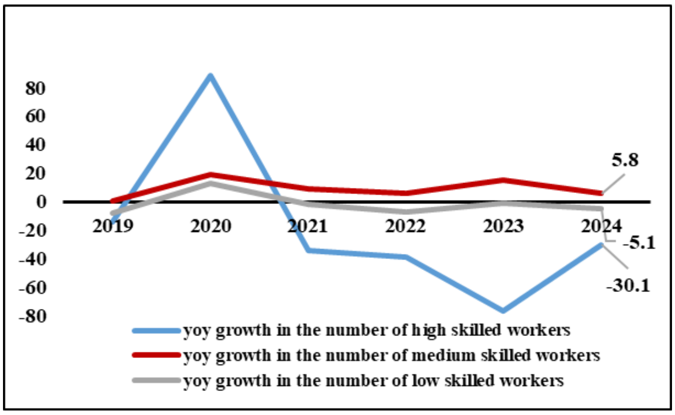


Source: PLFS (2018-2024); Authors' calculations.

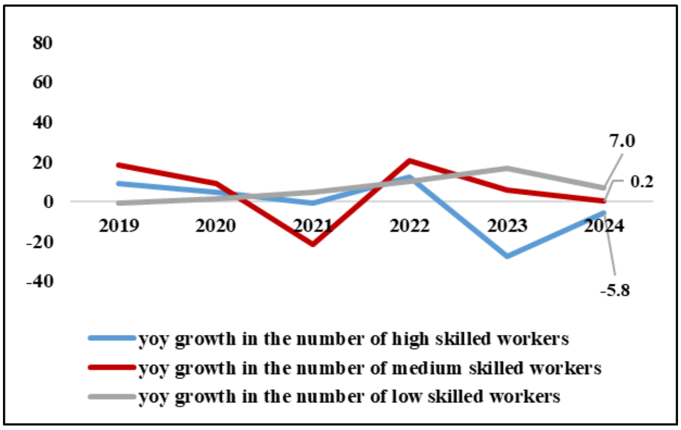
Note: i. The agriculture sector includes 2-digit industry codes from 01 to 03; the manufacturing sector includes 2-digit industry codes from 10 to 33; and the services sector includes 2-digit industry codes from 45 to 99; ii. Skill categorisation is based on NCO (1-digit level). iii. The weighted sample size in agriculture varies from 143.98 million in 2018 to 207.41 million in 2024, in manufacturing, it varies from 42.65 million in 2018 to 57.06 million in 2024, and in services, from 109.29 million in 2018 to 146.95 million in 2024.

As per Figure 3.3, year-on-year employment growth in the agriculture and services sectors has been highest for medium-skill jobs (except in 2024, where low skill employment showed the highest growth).

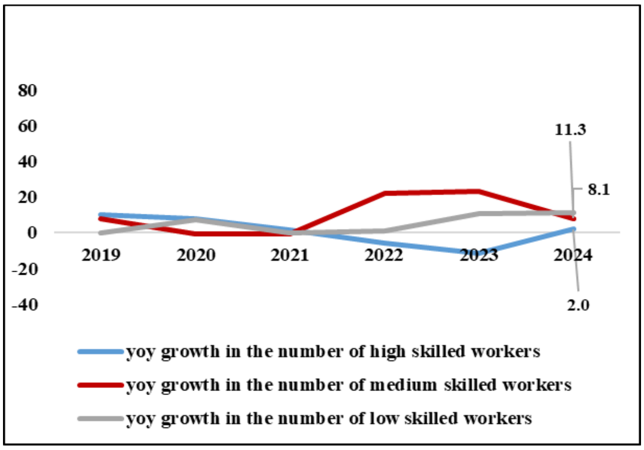
Figure 3.3: Y-o-Y growth in employment by skills for workers aged 15-59 years within agriculture, manufacturing, and services (%)



a) Agriculture



b) Manufacturing



c) Services

Source: PLFS (2018 to 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 categorisation is based on NCO (1-digit level); iii. The weighted sample size in agriculture varies from 143.98 million in 2018 to 207.41 million in 2024, in manufacturing, it varies from 42.65 million in 2018 to 57.06 million in 2024, and in Services, from 109.29 million in 2018 to 146.95 million in 2024.

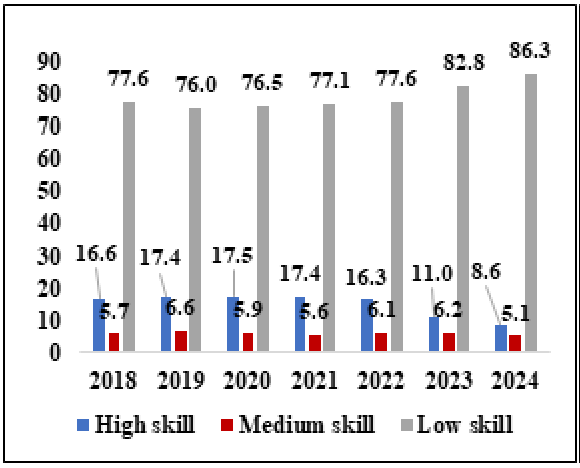
Within manufacturing, low-skill employment has shown the highest growth for the last two years. Although high-skill employment declined across all the three sectors from 2018 to 2023, it began to rise again between 2023 and 2024.

3.2.1. Skill distribution within the labour-intensive sectors

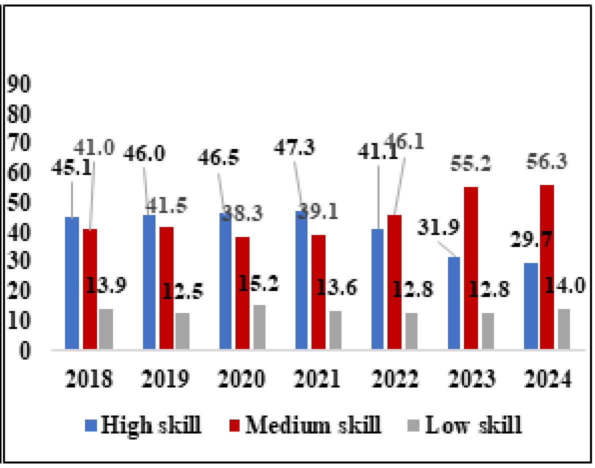
The ranking of labour-intensive manufacturing industries is based on calculation of L/K ratio using RBI KLEMS data. The labour-intensive manufacturing sector includes Food and Beverages and Tobacco; Textiles, Textile Products and Leather, and Footwear; and Manufacturing (nec), Recycling. The labour-intensive service sector includes Trade; Hotels and Restaurants; Education; and the Health and Social Work sector. On average, labour-intensive manufacturing accounts for 44.1 per cent of the total manufacturing employment, while labour-intensive services account for 54.2 per cent of total services employment. Combined, the labour-intensive sectors constitute 51.3 per cent of total employment in manufacturing and services. When considered as a share of total non-farm employment, the contribution of labour-intensive sectors is slightly lower, at 39 per cent, suggesting that a portion of non-farm employment lies outside the manufacturing and services sectors.

As per Figure 3.4, the labour-intensive manufacturing sector is dominated by low skilled employment. However, the labour-intensive services sector is dominated by medium skilled workers.

Figure 3.4: Employment distribution by skills within labour-intensive sectors for workers aged 15-59 years (%)



a) Labour-intensive manufacturing



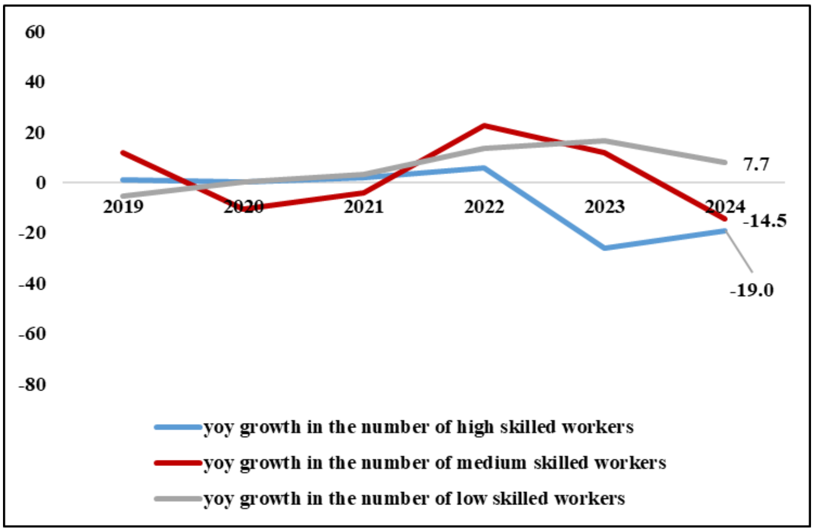
b) Labour-intensive services

Source: PLFS (2018 to 2024); Authors' calculations.

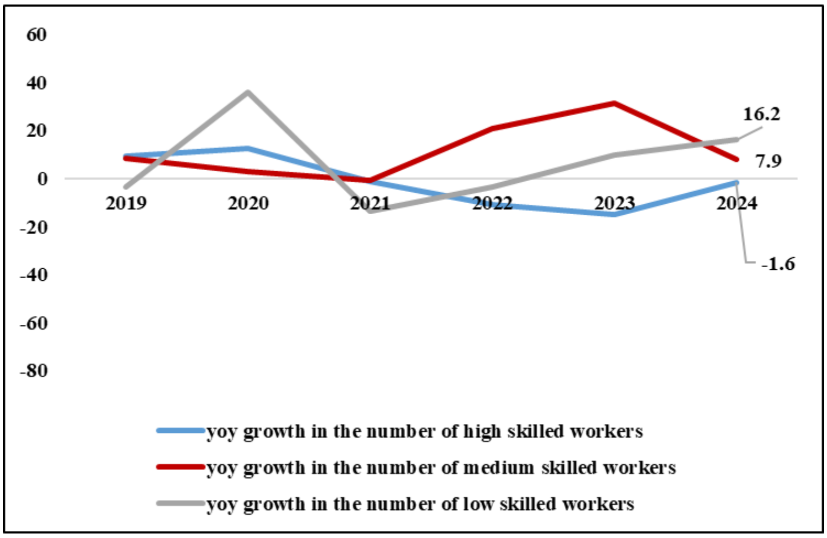
Note: i. The classification of labour-intensive sectors is based on a high labour-to-capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data in Section 2; ii. For labour-intensive manufacturing, the weighted sample size varies from 19.95 million in 2018 to 25.04 million 2024, and for labour-intensive services it varies from 57.68 million in 2018 to 79.55 million in 2024.

As per Figure 3.5, year-on-year employment growth in labour-intensive services is mostly the highest for medium-skilled workers. However, in 2024, growth was higher for low-skilled employment within labour-intensive services. In labour-intensive manufacturing, low-skilled workers recorded the highest employment growth.

Figure 3.5: Y-o-Y growth in employment by skills for workers aged 15–59 years within labour-intensive sectors (%)



a) Labour-intensive manufacturing



b) Labour-intensive services

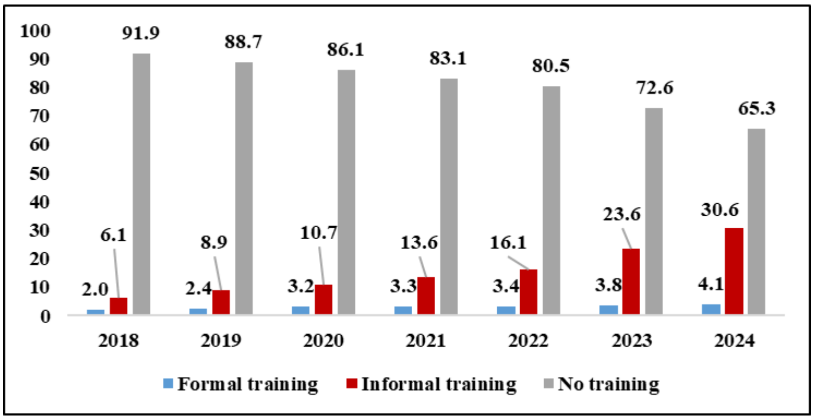
***Source**:* PLFS (2018 to 2024); Authors' calculations.
***Note**:* i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. For labour-intensive manufacturing, the sample size varies from 19.95 million in 2018 to 25.08 million 2024 and for labour-intensive services it varies from 57.68 million in 2018 to 79.55 million in 2024.

3.3. Supply of Skills

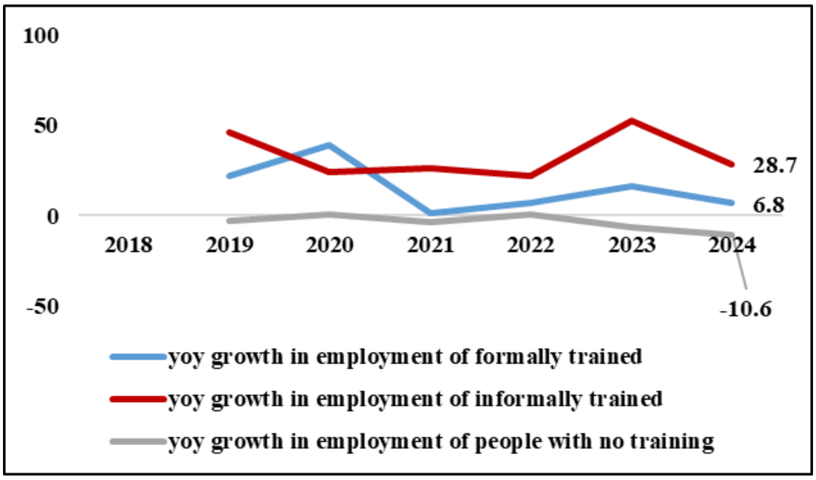
3.3.1. Supply of skills at an aggregate economy level

As per Figure 3.6, there has been a decline in the share of untrained workers over time. In 2018, 92 per cent of the workers had no training, which fell to 65 per cent by 2024. However, the majority of workers remain untrained. As of 2024, only 4 per cent of the workers had received formal training. Moreover, the year-on-year (Y-o-Y) growth in the number of formally trained workers is lower than the growth in the number of informally trained workers (refer to footnote of Figure 3.6 for types of training included in the informal categories).

Figure 3.6: Distribution of workers aged 15-59 years by training (%)



a) Distribution of employment by training



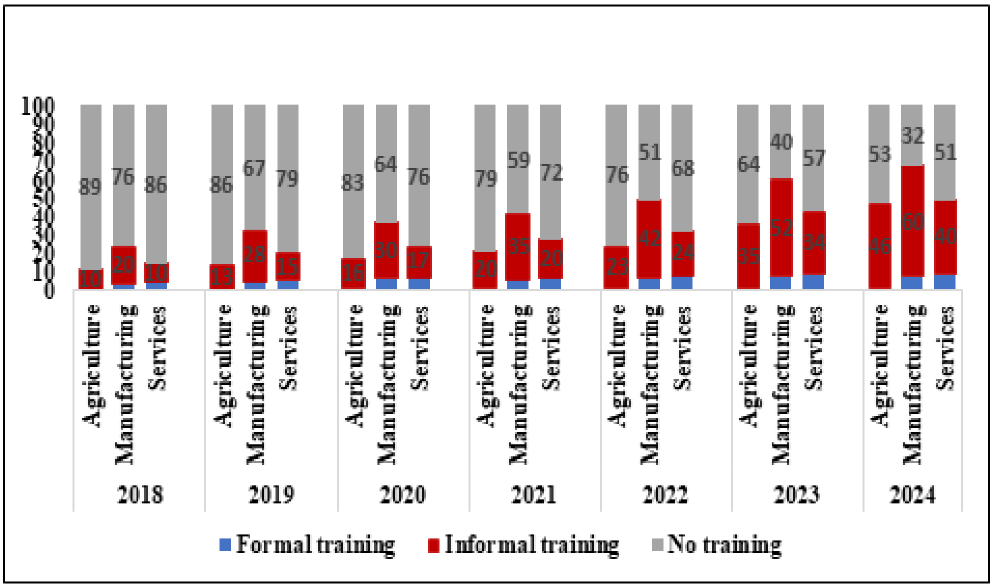
b) Y-o-Y growth in employment by training

Source*:* PLFS (2018 to 2024); Authors' calculations.
Note: i. Informal training includes hereditary, self-learning, learning on the job, and other types of training; ii. Weighted sample size varies from 688 million in 2018 to 765 million in 2024.

3.3.2. Supply of skills within agriculture, manufacturing and services

Figure 3.7 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 per cent.

Figure 3.7: Workforce distribution by training within agriculture, manufacturing, and services (%)

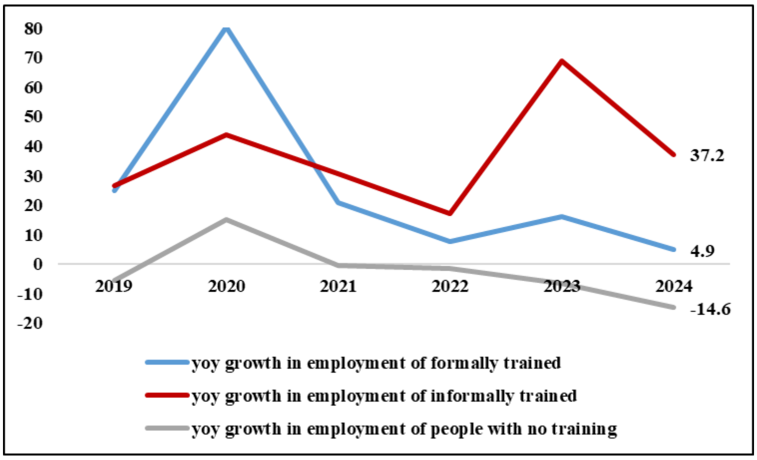


Source: PLFS (2018 to 2024); Authors' calculations.

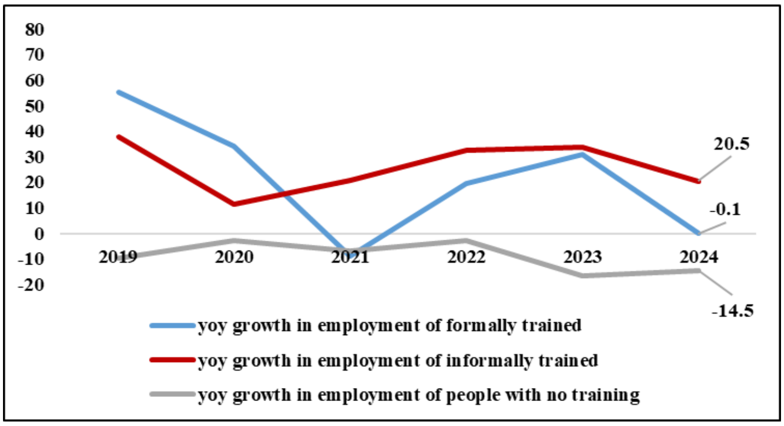
Note: i. The agriculture sector includes 2-digit industry codes from 01 to 03; the manufacturing sector includes 2-digit industry codes from 10 to 33; and the services sector includes 2-digit industry codes from 45 to 99; ii. Informal training includes hereditary, self-learning, learning on the job, and other types of training; iii. Weighted sample size within agriculture varies from 143 million in 2018 to 207 million in 2024; weighted sample size within manufacturing varies from 43 million in 2018 to 57 million in 2024; weighted sample size within services varies from 109 million in 2018 to 147 million in 2024.

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 (Figure 3.8). The growth in the number of formally and informally trained workers came down between 2022-23 and 2024 in all the three sectors.

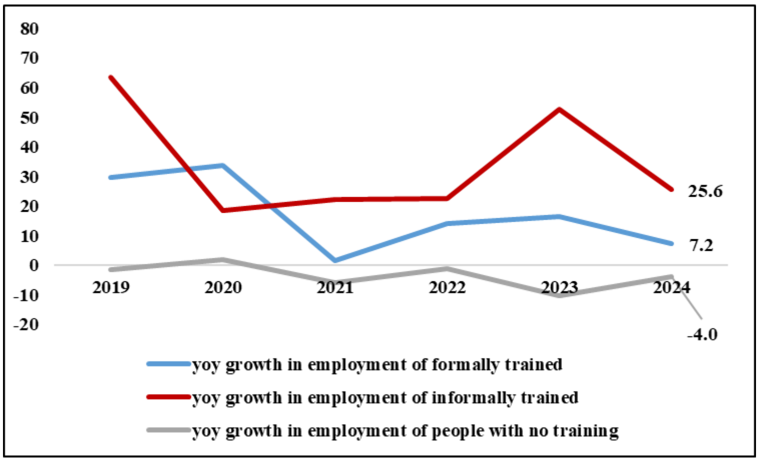
Figure 3.8: Y-o-Y growth in workers aged 15–59 years by training status within the agriculture, manufacturing, and services sectors (%)



a) Agriculture



b) Manufacturing



(c) Services

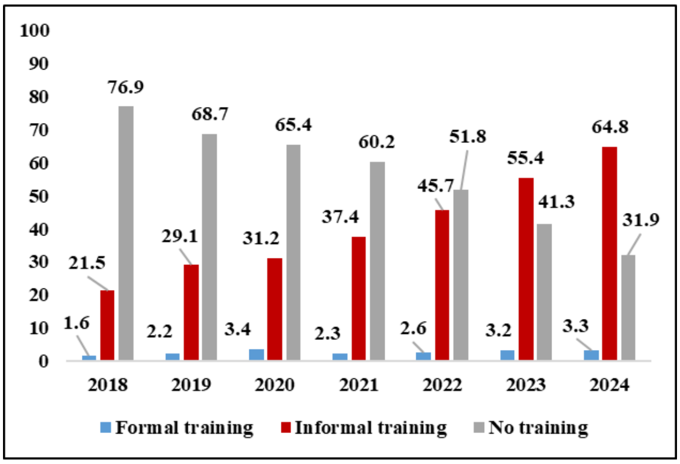
Source: PLFS (2018 to 2024); Authors' calculations.

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 varies from 143 million in 2018 to 207 million in 2024; weighted sample size within manufacturing varies from 43 million in 2018 to 57 million in 2024; weighted sample size within services varies from 109 million in 2018 to 147 million in 2024.

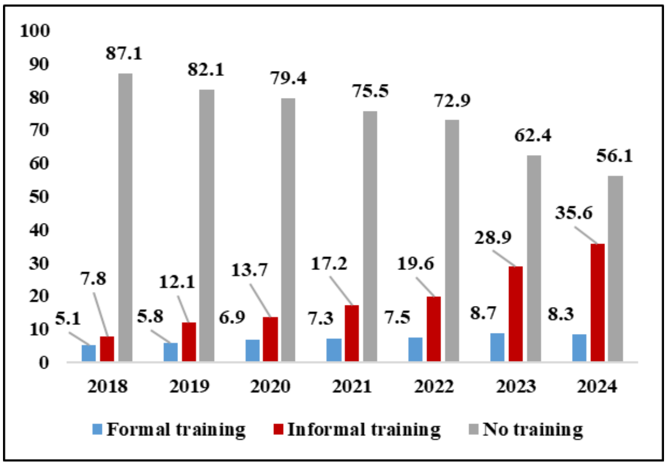
3.3.3. Supply of skills within the labour- intensive sectors

The labour-intensive services sector is dominated by untrained workers. Labour-intensive manufacturing is dominated by informally trained workers (Figure 3.9).

Figure 3.9: Workforce distribution by training within the labour-intensive sectors for the age group of 15-59 years (%)



a) Labour-intensive manufacturing

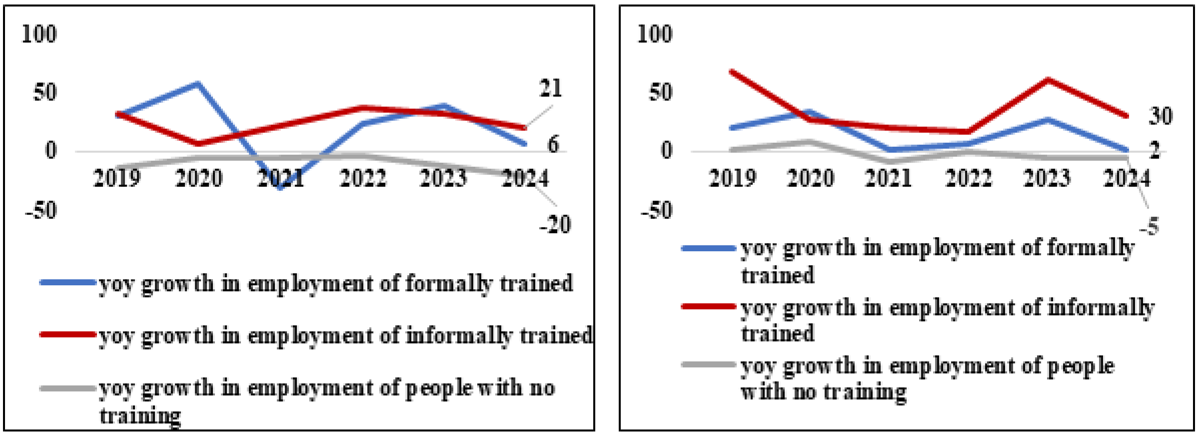


b) Labour-intensive services

Source*:* PLFS (2018 to 2024); Authors' calculations.
Note*:* i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. For labour-intensive manufacturing, the sample size varies from 19.95 million in 2018 to 25.08 million 2024 and for labour-intensive services it varies from 57.68 million in 2018 to 79.55 million in 2024.

As per Figure 3.10, the Y-o-Y growth in the formally trained workforce was lower than that of the informally trained workforce, within both the manufacturing and services labour-intensive sectors, as of 2024. Moreover, the overall growth in trained individuals declined between 2023 and 2024, in both the labour-intensive sectors.

Figure 3.10: Y-o-Y growth in workers aged 15-59 years by training within the labour-intensive sectors (%)



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

***Source**:* PLFS (2018 to 2024); Authors' calculations.
***Note**:* i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. For labour-intensive manufacturing, the sample size varies from 19.95 million in 2018 to 25.08 million 2024, and for labour-intensive services it varies from 57.68 million in 2018 to 79.55 million in 2024.

3.4. Demand and Supply Mismatch

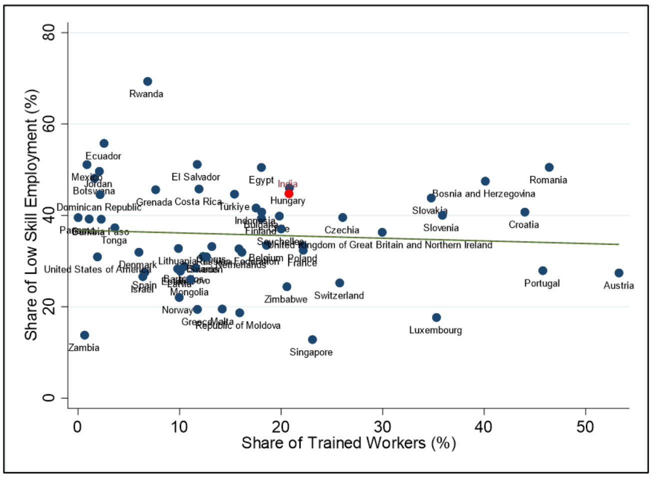
Section 3.2 shows that most employment is being generated in medium-skill industries. Section 3.3 highlights that India has a relatively small proportion of trained workers, particularly those with formal training. However, as the economy evolves and the demand for high-skilled employment increases, it will be crucial to expand the share of trained workers, especially those who are formally trained.

To support this argument, cross-country data on the share of trained workers and the distribution of employment by skill level (high, medium, and low) is presented in Section 3.4.1. This is followed by our estimations in Section 3.4.2, which show that training, particularly formal training, increases the probability of being employed, especially in high-skill jobs.

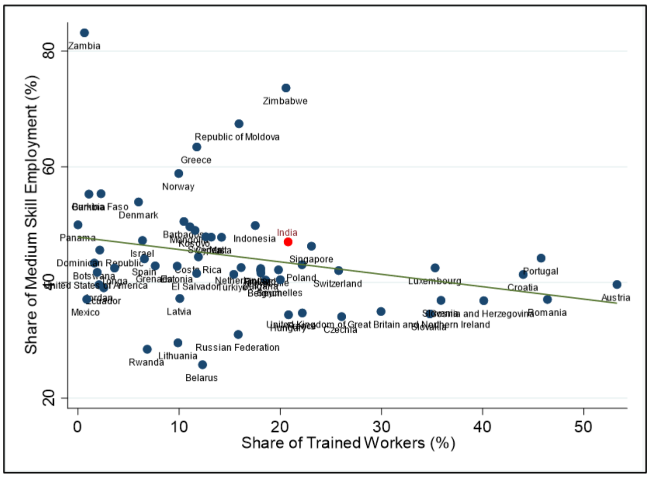
3.4.1. Cross-country comparisons

Figure 3.11 suggests a positive association between the share of trained workers and the share of high-skill employment, alongside a negative association with both medium- and low-skill employment.

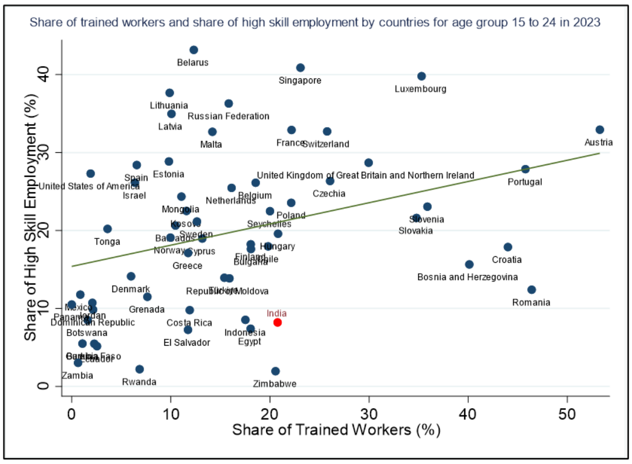
Figure 3.11: Share of trained workers and share of low, medium and high skill employment for the age group of 15-24 years in 2023 (%)



a) Share of low-skill employment



b) Share of medium-skill employment



c) Share of high-skill employment

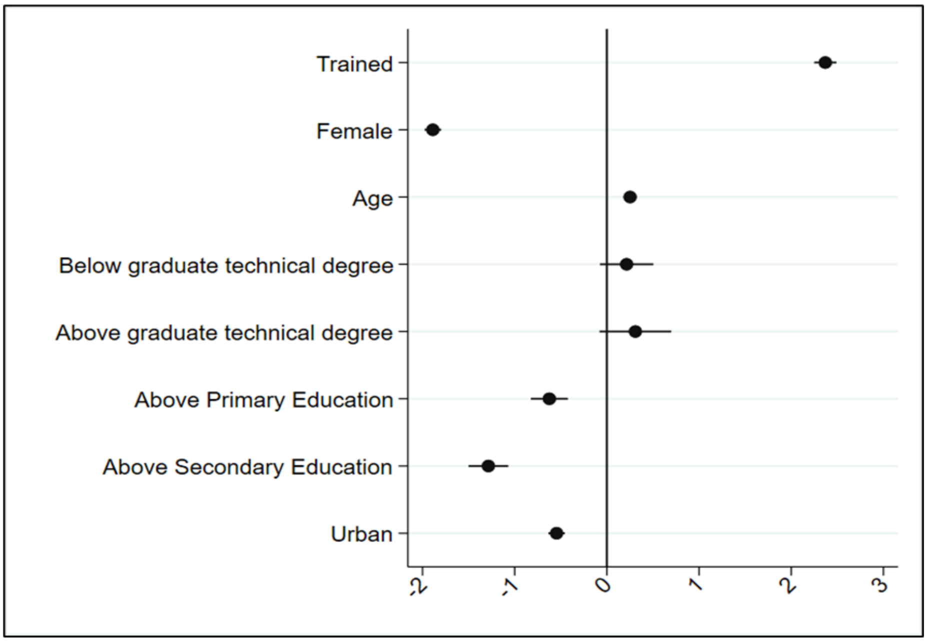
Source: ILOSTAT, International Labour Organization (2023); Authors' calculations.
Note: i. ILOSTAT data allow calculation of the share of youth (15–24 years) with vocational training across countries; ii. ILOSTAT also reports data on employment by occupation skill level; iii. Sample size is 58 countries.

The charts in Figure 3.11 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 3.3 showed, much of the existing training in India is informal, which may limit its effectiveness in improving high-skilled employment.

3.4.2. Estimations

Figure 3.12 shows the log-odds of being employed in any job, based on whether the individual is trained or not, for 2024. The results indicate that having vocational training and technical education is positively associated with the odds of being employed. Among these, vocational training has the strongest and most statistically significant effect on the likelihood of employment. The regression model and explanatory variables used in this analysis are detailed in Annexure A3, Section A3.2.1.

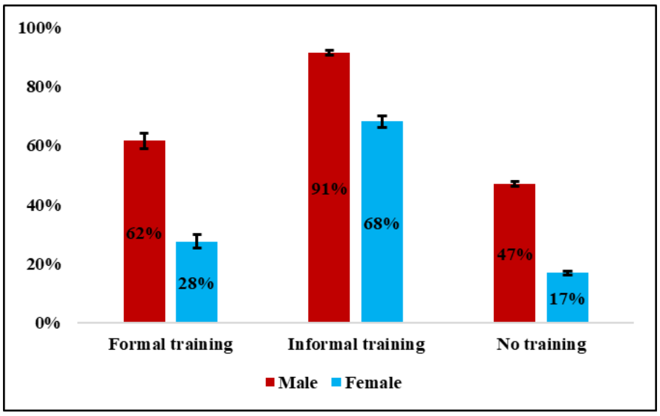
Figure 3.12: Log (Odds) of being employed in any job in 2024 for workers aged 15–29 years



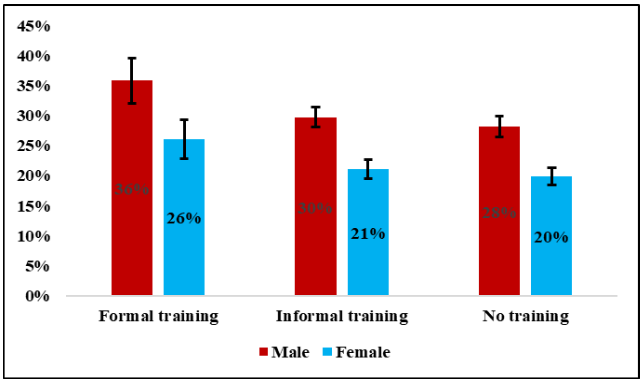
Source: PLFS (2024); Authors' calculations.
Note: i. *Log (Odds)* is derived from a logit regression equation A3.1, as explained in Annexure A3.2.1, using PLFS data (2018 to 2024). The regression models the likelihood of a worker being employed in any job as a function of whether the worker is trained, years of general education, type of technical education received, age, location (rural/urban), and state fixed effects, for individuals aged 15-29 years; ii. Coefficients are plotted with 99 per cent confidence bands; iii. The weighted number of observations for the regression is 109,048.

Figure 3.13 presents the predicted probabilities of being employed in any job, in a regular salaried job, and in a high-skill job, based on training status.

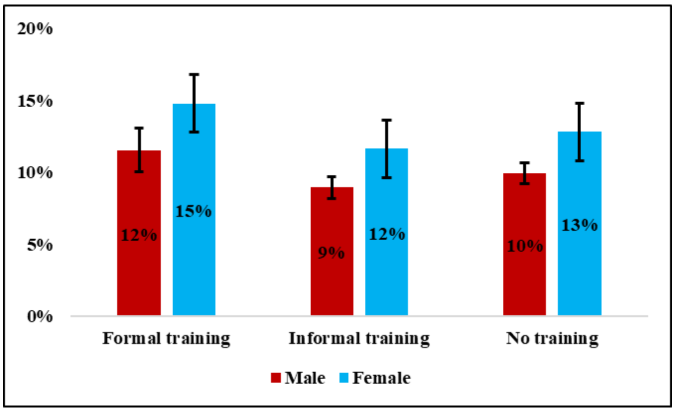
Figure 3.13: Predicted probability of being employed based on training level of worker aged 15-29 years in 2024 (%)



(a) Employed in any job



(b) Employed in regular jobs



(c) Employed in high-skilled job

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

The confidence intervals shown for each predicted probability indicate whether the differences between trained and untrained individuals are statistically significant. Figure 3.13 shows 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. In contrast, informal training 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 programmes 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.

3.5. Simulations to Assess the Impact of Increased Formal Vocational Training on Employment

The detailed methodology for simulations is shown in Annexure A3.2.2.

Based on varying growth of share of formally trained workers, different simulated scenarios are assumed in simulation 1:

1. *Baseline:* It is assumed that the Y-o-Y growth in the number of formally trained workers and the number of total workers is the same as the average y-o-y growth from 2018 to 2024 (excluding 2021), in each of the projected years from 2025 to 2030.
2. *Moderate increase in the number of formally trained workers:* It is assumed that the Y-o-Y growth in the number of formally trained workers is 0.5 SD greater than the average Y-o-Y growth in the number of formally trained workers and the number of total workers is the same as the average Y-o-Y growth from 2018 to 2024 (excluding 2021), in each of the projected five years from 2025 to 2030.
3. *High growth in the number of formally trained workers*: It is assumed that the y-o-y growth in the number of formally trained workers is 1 SD greater than the average y-o-y growth in the number of formally trained workers and the number of total workers is the same as the average y-o-y growth from 2018 to 2024 (excluding 2021), in each of the projected five years from 2025 to 2030.

Based on varying growth of share of formally trained workers and varying marginal effect obtained from logit model, different scenarios are assumed as part of simulation 2:

1. *Baseline*: It is assumed that the Y-o-Y growth in the number of formally trained workers and the number of total workers is the same as the average Y-o-Y growth from 2017-18 to 2023-24, in each of the projected years from 2024-25 to 2029-30 (excluding 2020-21) and impact of formal training on employment is taken from a statistical model (Table A3.1 in Annexure A3), which estimates how much formal training increases a person's chances of being employed.
2. *Moderate increase in the marginal effect of being trained:* It is assumed that the Y-o-Y growth in the number of formally trained workers and the number of total workers is the higher than the average y-o-y and the impact of formal training on employment is assumed to be 0.5 standard errors higher than the marginal effect estimated from the model (Table A3.1 in Annexure A3) that relates formal training to the probability of being employed.
3. *High growth in the number of formally trained workers*: It is assumed that the Y-o-Y growth in the number of formally trained workers and the number of total workers is higher than the average Y-o-Y growth by 1 SD and the impact of formal training on employment is assumed to be 1 standard errors higher than the marginal effect

estimated from the model (Table A3.1 in Annexure A3) that relates formal training to the probability of being employed.

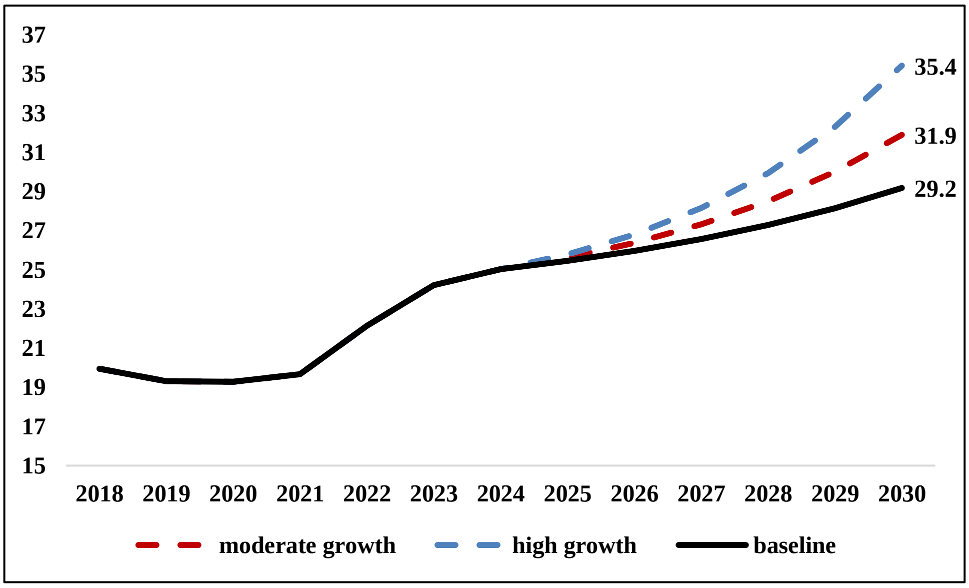
3.5.1. Estimation for the labour-intensive manufacturing sector

As of the base year 2024, the number of employed persons in labour-intensive manufacturing stands at 25 million.

Figure 3.14 and Table 3.1 show the following results based on simulation 1:

- *Under the baseline scenario*, the share of formally trained workers is projected to increase from 4 per cent to 9 per cent (a rise of 5 pp points) by 2030. The addition to the number of jobs in labour-intensive manufacturing is expected to be around 4.1 million relative to the base year (Column 4 of Table 3.1). This represents a 16.6 per cent increase in employment as compared to 2024, within labour-intensive manufacturing (Column 5 of Table 3.1).
- Under the moderate growth scenario, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 13 per cent by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 6.9 million relative to the base year (Column 4 of Table 3.1) representing a 27.4 per cent increase, within labour-intensive manufacturing (Column 5 of Table 3.1).
- Under the high growth scenario, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 16 per cent by 2030 (a rise of 12 pp points). The cumulative addition to jobs is projected to be around 10.4 million (Column 4 of Table 3.1), representing a 41.5 per cent increase over the base year (Column 5 of Table 3.1).

Figure 3.14: Employment in labour-intensive manufacturing (ages 15–59 years) under different scenarios based on simulation 1 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2024-25 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases in the moderate and high growth scenarios as compared to the baseline.

Table 3.1: Cumulative addition to jobs in labour-intensive manufacturing under different scenarios based on simulation 1

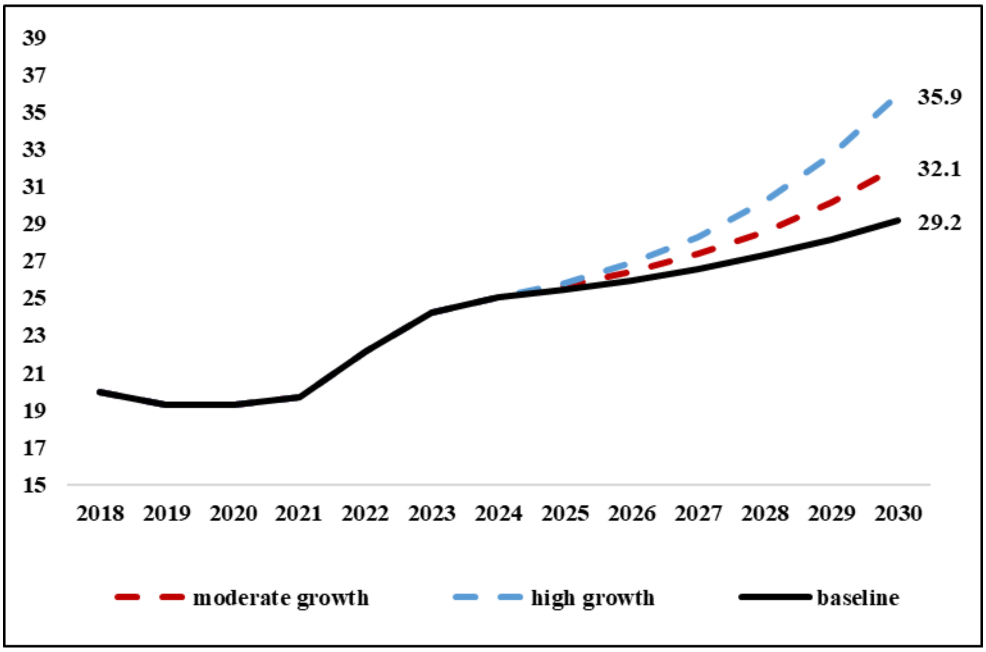
Scenario	Employment in labour intensive manufacturing in 2024 (millions)	Employment in labour intensive manufacturing in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce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

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.*2*; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases in the moderate and high growth scenarios as compared to the baseline.

Figure 3.15 and Table 3.2 show the following results based on simulation 2:

- *Under the baseline scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 9 per cent by 2030 (a rise of 5 pp) and the marginal impact of being formally trained on employment in manufacturing is taken to be 0.085. The addition to the number of jobs in labour-intensive manufacturing is expected to be around 4.1 million relative to the base year (Column 4 of Table 3.2). This represents a 16.6 per cent increase in employment as compared to 2024, within labour-intensive manufacturing (Column 5 of Table 3.2).
- *Under the moderate growth scenario*, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 13 per cent by 2030 (an increase of 9 pp) and the marginal impact of being formally trained on employment manufacturing is taken to be 0.087. The expected addition to jobs is 7 million relative to the base year (Column 4 of Table 3.2), representing a 28.1 per cent increase within labour-intensive manufacturing (Column 5 of Table 3.2).
- *Under the high growth scenario*, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 16 per cent by 2030 (an increase of 12 pp) and the marginal impact of being formally trained on employment in manufacturing is taken to be 0.089. The cumulative addition to jobs is projected to be around 10.9 million (Column 4 of Table 3.2), representing a 43.5 per cent increase over the base year, within labour-intensive manufacturing (Column 5 of **Table 3.2**).

Figure 3.15: Employment in labour-intensive manufacturing (ages 15-59 years) under different scenarios based on simulation 2 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2024-25 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

Table 3.2: Cumulative addition to jobs in labour-intensive manufacturing under different scenarios based on simulation 2

Scenario	Employment in labour intensive manufacturing in 2024 (millions)	Employment in labour intensive manufacturing in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)	Marginal impact of training on employment in manufacturing
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Baseline	25.0	29.2	4.1	16.6	4	9	0.085
Moderate Growth	25.0	32.1	7.0	28.1	4	13	0.087
High Growth	25.0	35.9	10.9	43.5	4	16	0.089

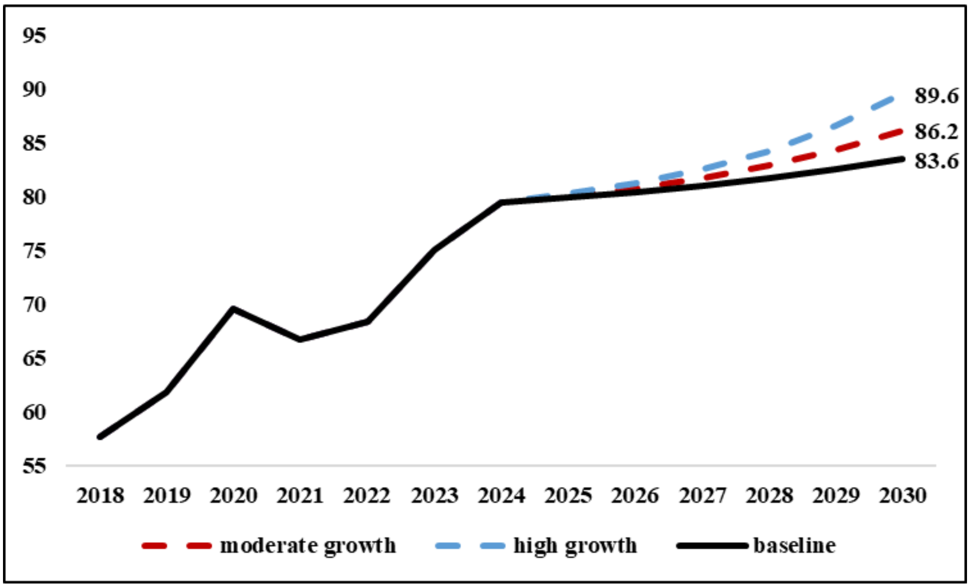
Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

3.5.2. Estimation for the labour-intensive services sector

As of the base year 2024, the number of employed persons in labour-intensive services stand at 79 million. Figure 3.16 and Table 3.3 show the following results based on simulation 1:

- *Under the baseline scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 9 per cent by 2030 (a rise of 5 pp points). The addition to the number of jobs in labour-intensive services is expected to be around 4 million, relative to the base year (Column 4 of Table 3.3). This represents a 5.1 per cent increase in employment as compared to 2024 (Column 5 of Table 3.3).
- *Under the moderate growth scenario*, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 13 per cent by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 6.6 million, relative to the base year (Column 4 of Table 3.3), representing an 8.4 per cent increase (Column 5 of Table 3.3).
- *Under the high growth scenario*, the share of formally trained workers is projected to rise from 4 per cent in 2024 to 16 per cent by 2030 (an increase of 12 pp points). The cumulative addition to jobs is projected to be around 10.1 million (Column 4 of Table 3.3), corresponding to a 12.7 per cent increase over the base year (Column 5 of Table 3.3).

Figure 3.16: Employment in labour-intensive services (ages 15-59 years) under different scenarios based on simulation 1 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases in the moderate and high growth scenarios as compared to the baseline.

Table 3.3: Cumulative addition to jobs in labour-intensive services under different scenarios based on simulation 1

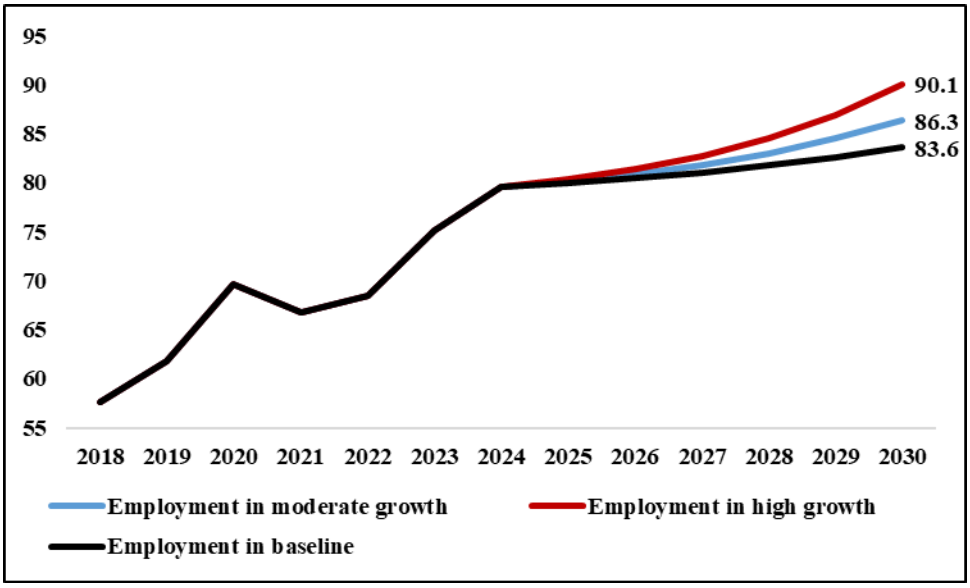
Scenario	Employment in labour-intensive services in 2024 (millions)	Employment in labour-intensive services in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in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

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases in the moderate and high growth scenarios as compared to the baseline.

Figure 3.17 and Table 3.4 show the following results based on simulation 2:

- *Under the baseline scenario,* the share of formally trained workers is projected to increase from 4 per cent in 2024 to 9 per cent by 2030 (a rise of 5 pp points) and the marginal impact of being formally trained on employment in services is taken to be 0.083. The addition to the number of jobs in labour-intensive services is expected to be around 4.0 million, relative to the base year (Column 4 of Table 3.4). This represents a 5.1 per cent increase in employment as compared to 2024 (Column 5 of Table 3.4).
- *Under the moderate growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 13 per cent by 2030 (an increase of 9 pp points) and the marginal impact of being formally trained on employment in services is taken to be 0.085. The expected addition to jobs is approximately 6.8 million, relative to the base year (Column 4 of Table 3.4), representing an 8.5 per cent increase (Column 5 of Table 3.4).
- *Under the high growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 16 per cent by 2030 (an increase of 12 pp points) and the marginal impact of being formally trained on employment in services is taken to be 0.087. The cumulative addition to jobs is projected to be around 10.5 million (Column 4 of Table 3.4), corresponding to a 13.2 per cent increase over the base year (Column 5 of Table 3.4).

Figure 3.17: Employment in labour-intensive services (ages 15-59 years) under different scenarios based on simulation 2 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

Table 3.4: Cumulative addition to jobs in labour-intensive services under different scenarios based on simulation 2

Scenario	Employ-ment in labour-intensive services in 2024 (millions)	Employ-ment in labour-intensive services in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)	Marginal impact of training on employ-ment in services
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Baseline	79.6	83.6	4.0	5.1	4	9	0.083
Moderate Growth	79.6	86.3	6.8	8.5	4	13	0.085
High Growth	79.6	90.1	10.5	13.2	4	16	0.087

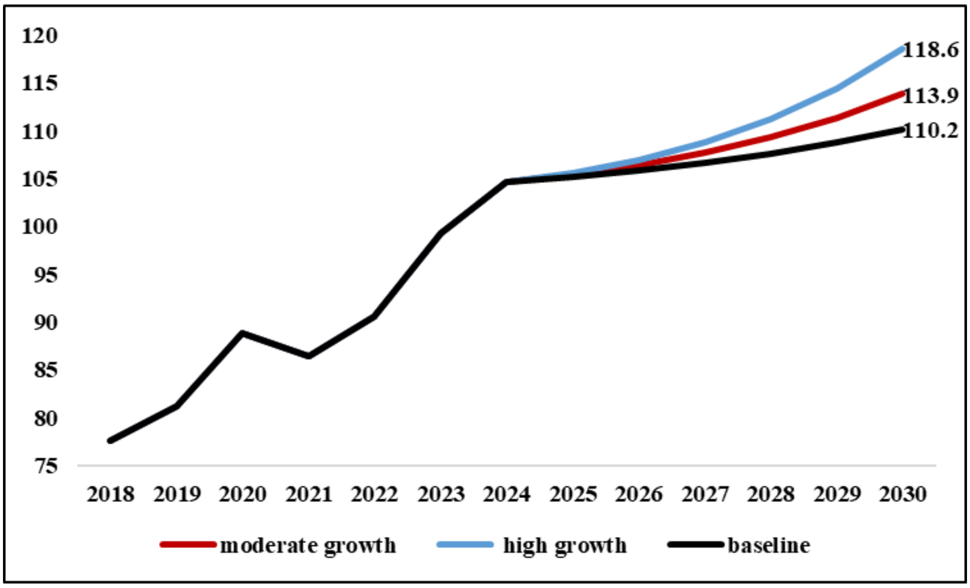
Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

3.5.3. Estimations for aggregate labour-intensive sectors

As of the base year 2024, the number of total employed persons in the labour-intensive manufacturing and services sectors stand at 104 million. Figure 3.18 and Table 3.5 show the following results of the simulation 1:

- *Under the baseline scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 9 per cent by 2030 (a rise of 5 pp points). The addition to the number of jobs in the labour-intensive sectors is expected to be around 5.6 million relative to the base year (Column 4 of Table 3.5). This represents a 5.4 per cent increase in employment as compared to 2024 (Column 5 of Table 3.5).
- *Under the moderate growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 13 per cent by 2030 (an increase of 9 pp points). The expected addition to jobs is approximately 9.3 million, relative to the base year (Column 4 of Table 3.5), representing an around 8.9 per cent increase (Column 5 of Table 3.5).
- *Under the high growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2024 to 16 per cent by 2030 (an increase of 12 pp points). The cumulative addition to jobs is projected to be around 14 million (Column 4 of Table 3.5) corresponding to a 13.4 per cent increase over the base year (Column 5 of Table 3.5).

Figure 3.18: Employment in aggregate labour-intensive sectors (ages 15-59 years) under different scenarios based on simulation 1 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases in the moderate and high growth scenarios as compared to the baseline.

Table 3.5: Cumulative addition to jobs in the labour-intensive sectors under different scenarios based on simulation 1

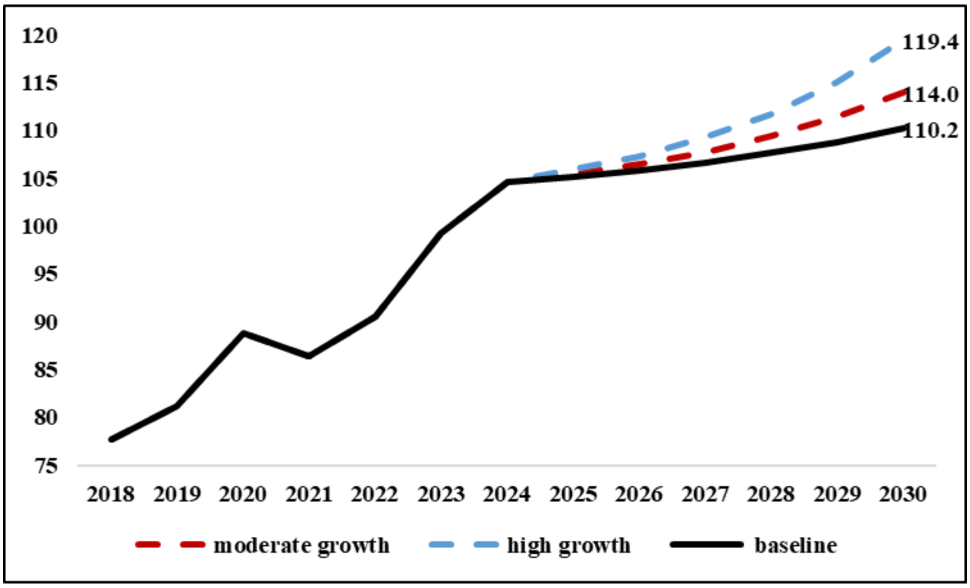
Scenario	Employment in labour intensive sector in 2024 (millions)	Employment in labour-intensive sector in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030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

***Source**:* PLFS (2018 to 2024); Authors' calculations.
***Note**:* i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

Figure 3.19 and Table 3.6 show the following results based on simulation 2:

- *Under the baseline scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2023-24 to 9 per cent by 2029–30 (a rise of 5 pp points) and the marginal impact of training on total employment in the manufacturing and services sectors is taken as 0.115. The addition to the number of jobs in labour-intensive sectors is expected to be around 5.6 million, relative to the base year. This represents a 5.4 per cent increase in employment as compared to 2023–24.
- *Under the moderate growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2023-24 to 13 per cent by 2029-30 (an increase of 9 pp points) and the marginal impact of training on total employment in the manufacturing and services sectors is taken as 0.117. The expected addition to jobs is approximately 9.4 million, relative to the base year, representing an increase of around 9 per cent.
- *Under the high growth scenario*, the share of formally trained workers is projected to increase from 4 per cent in 2023-24 to 16 per cent by 2029-30 (an increase of 12 pp points) and the marginal impact of training on total employment in the manufacturing and services sectors is taken as 0.119. The cumulative addition to jobs is projected to be around 14.8 million corresponding to a 14.2 per cent increase over the base year.

Figure 3.19: Employment in the aggregate labour-intensive sectors (ages 15-59 years) under different scenarios based on simulation 2 (millions)



Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

Table 3.6: Cumulative addition to jobs in the aggregate labour-intensive sector under different scenarios based on simulation 2

Scenario	Employment in the labour-intensive sector in 2024 (millions)	Employment in the labour-intensive sector in 2030 (millions)	Jobs created between 2030 and 2024 (millions)	Increase in jobs between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)	Marginal impact of training on employment in the labour-intensive sectors
(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Baseline	104.6	110.2	5.6	5.4	4	9	5
Moderate Growth	104.6	114.0	9.4	9.0	4	13	9
High Growth	104.6	119.4	14.8	14.2	4	16	12

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The projections are based on a simulation model detailed in Annexure A3.2.2; iii. Employment gains from 2025 to 2030 reflect increasing shares of formally trained workers across all scenarios, with larger increases and higher marginal impacts in the moderate and high growth scenarios as compared to the baseline.

3.5.4. Estimations for labour-intensive sectors based on the government target for employment

Do the growth scenarios achieve the government's employment 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 Economic Survey accounts for both the expected increase in the workforce and a decline in the share of the workforce engaged in agriculture. Specifically, using this government target, we assess:

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

We make certain key assumptions:

- Untrained workers are assumed to grow at the average Y-o-Y growth rate observed from 2018 to 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 labour-intensive sectors (within manufacturing and services) to total non-farm employment of 39 per cent.

- The target of job creation for the labour-intensive sectors is, therefore, (78,00,000*0.39) 30,92,900 or 3.09 million per year. Over six years (2025 to 2030), this results in a cumulative employment requirement of 18.5 million new jobs.

The results (Table 3.7) suggest that in order to meet the Economic Survey target—adjusted for the labour-intensive manufacturing and services sectors—the share of the formally trained workforce should increase to around 20 per cent by 2030, as compared to 5.4 per cent 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 per cent 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 labour-intensive sectors within manufacturing and services, the required increase is much higher (refer to Annexure A3.2.3).

Table 3.7: Projected share of formally trained workers if the adjusted Economic Survey target is met

Scenario	Employment in the labour-intensive sectors in 2024 (millions)	Employ-ment in the labour-intensive sectors in 2030 (millions)	Total 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 (%)
Baseline	104.6	110.2	5.6	5.4	4	9
Scenario in which target is met	104.6	123.2	18.6	17.7	4	20

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The employment target is based on the Economic Survey's goal of creating 7.8 million non-farm jobs annually until 2030, adjusted for the average 39 per cent share of labour-intensive sectors (within manufacturing and services) in total non-farm employment; iii. The required increase in the share of formally trained workers is estimated using Equation 3.4 that links formal training to employment, in order to meet the Economic Survey target.

3.6. Vocational Education and Training (VET) Systems

3.6.1. Introduction to VET systems in Germany, Canada and Singapore

In Germany, VET is offered at the upper secondary level through a dual system combining school and paid apprenticeships. Canada provides VET at the short-cycle tertiary level via community colleges and polytechnics using co-operative education. Singapore delivers a dual vocational track system, with Institutes of Technical Education (ITE) at post-secondary level and Polytechnics at tertiary level, and complements this with lifelong learning through its Skills Future initiative. Despite the differences, these systems converge on three pillars: strong public investment, deep employer engagement, and institutional frameworks that ensure the portability of skills. The specific features of these systems, including funding structures, channel of employer engagement, and skill transferability, are summarised in Table 3.8. The association of the VET programmes with the labour market outcomes in these countries is explained in Box B3.

Table 3.8: Key Features of VET Systems in Germany, Canada, and Singapore

Country	VET Level (ISCED)	Key Features	Stakeholder Roles	Govt. Spending	Skill Portability channel
Germany	Upper Secondary (ISCED 3)	Dual system: school + workplace	- Government funds schools - Employers pay apprentices and co-design curriculum	12 % of total education expenditure on upper secondary VET (2020)	Skills recognised under National Skills Qualification Framework
Canada	Short-cycle Tertiary (ISCED 5)	Co-op education in colleges and polytechnics	- Government funds institutions - Employers pay apprentices, bear training cost and co-design curriculum	10% of total education expenditure on short-cycle tertiary VET (2020)	Work-integrated credentials
Singapore	Post-secondary non-tertiary (ISCED 4) and Short-cycle Tertiary (ISCED 5)	Dual vocational tracks (ITE and Polytechnics) + Skills Future	- Government funds ITEs/Polytechnics and gives Skills Future credits - Employers co-fund training	13% of total education expenditure on post- secondary VET (2020)	Defined pathways to higher education: ITE → Polytechnic → University

Source: UNESCO Institute for Statistics (UIS); OECD *Education at a Glance Report 2023*; Ministry of Manpower and Ministry of Education, Singapore.
Note: ISCED refers to International Standard Classification of Education.

3.6.2. India's VET landscape

In India, VET is primarily offered at the post-secondary level through Industrial Training Institutes (ITIs) and Polytechnics. ITIs, under the Ministry of Skill Development and Entrepreneurship (MSDE), admit students after Class VIII or X for short-term courses (6 months to 2 years). Polytechnics, under the Ministry of Education (MoE), admit students after Class X and offer 3-year diploma programmes.

While the institutional coverage is extensive—with over 15,000 ITIs and 25 lakh sanctioned seats, actual enrolment is only around 16 lakhs, implying just 64 per cent seat utilisation. The overall placement rate was only 0.09 per cent, and lower in many states and trades (NITI Aayog, 2023). Additionally, VET graduates from ITIs and Polytechnics often end up in informal and low-paying jobs. Table 3.9 outlines the structural features and associated challenges that contribute to the low uptake and employment rates in India's VET system.

Table 3.9: Key features and challenges of India's VET system

Feature of Indian VET System	Key Issues
Perception and Pathways	Weak national and state-level branding for vocational education Course allocation not aligned with local industry demand or youth aspirations, lowering perceived value No credit transfer or academic progression opportunities to mainstream higher education
Industry Linkages	Micro, Small and Medium Enterprises (MSMEs) drive local jobs but do not engage with ITIs due to low capacity Sector Skill Councils (SSCs) lack state-level presence and integration with ITIs/ Polytechnics ITIs depend heavily on government funding, with minimal private sector input in funding infrastructure or bearing training cost.
Quality	Over one-third of ITI instructor posts are vacant as there are limited National Skill Training Institutes (NSTIs) Limited financial autonomy restricts routine operational decisions at ITIs/ Polytechnics Absence of regular monitoring system hinders quality checks ITI grading system lacks trainee feedback, is not institutionalized annually, and relies on unexperienced evaluators
Financial Viability	Low student fees reduce financial viability and underutilised seats lead to high cost per student Uniform funding to VET institutions ignores differences in their performance or local demand VET institutions lack autonomy to generate revenue
Public investment	VET receives only around 0.14% of India's total education spending.

3.6.3. New government schemes and alignment with the VET system

Recently announced government schemes in Budget 2024-25, such as ELI Part A and B, the PM Internship Scheme, and the ITI Upgradation Initiative, reflect an increasing focus on improving employment outcomes. Most interventions focus on hiring incentives in the formal sector or improving infrastructure. Table 3.10 assesses these schemes summarising their objectives, target beneficiaries, funding, critical design gaps, and alignment with VET dimensions.

Table 3.10: Assessment of new government schemes from a VET perspective

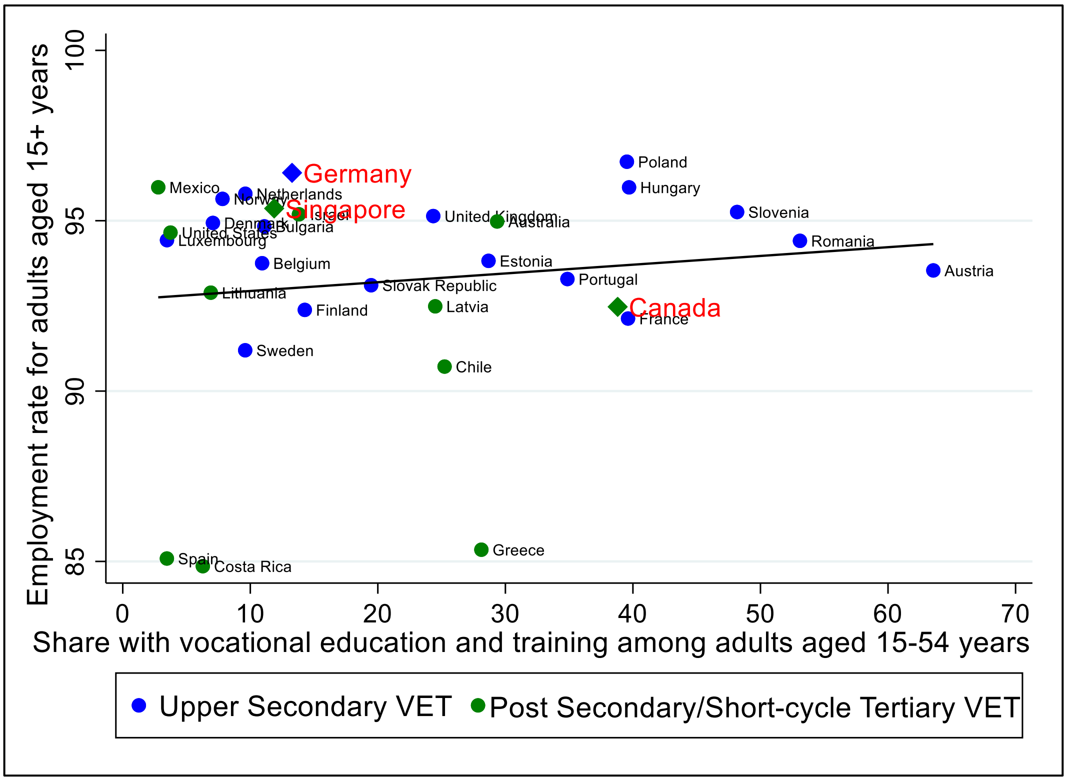
Scheme	What it Does	Target Sector	Target Beneficiaries	Duration of Benefit	Eligibility Criteria	Funding	Gaps (with regard to VET)
ELI Part A (Employee-focused)	Government provides a one-time incentive up to ₹15,000 to first-time EPFO-registered employees, paid in 2 parts: after 6 months and after 12 months, and after completion of a financial literacy programme	All formal sectors	1.92 crore first-time formal workers	1 year	Employee must be a first-time entrant into EPFO; continuous employment for 12 months	99,466 crores (total allocation for ELI scheme including Part A & B)	• Financial literacy program mandatory but no formal skilling • May not ensure long-term retention after benefits end
ELI Part B (Employer-focused)	₹3,000/month incentive paid to employers for each new EPFO-registered employee they hire	All formal sectors (esp. manufacturing)	Additional employment for 2.60 crore	2 years (4 years for manufacturing)	Employer must be EPFO-registered and hire ≥2 (if staff <50) or ≥5 (if staff ≥50); employee must stay ≥6 months	99,466 crores (shared with Part A)	• Incentivizes hiring without ensuring formal training • Incentive requires only 6-month retention and may not ensure stable jobs
Prime Minister Internship Scheme	Provides one-year internship to youth in top 500 companies over five years	All sectors	1 crore unemployed youth	1 year	Youth aged 21–24; not enrolled in full-time education	800 crores for pilot; shared cost by Government and Employers through CSR	• No formal certification or clear pathways to jobs • CSR-based funding may limit long-term scale and sustainability
ITI Upgradation Scheme	Hub-and-spoke model for ITI upgradation; upgrading 5 NSTIs	Industry-aligned vocational/technical trades (e.g., electronics, automotive, renewables)	20 lakh ITI students and 50,000 trainers	5 years	1,000 government ITIs	60,000 crore (30,000 crore Centre + ₹20,000 crore State+10,000 crore Industry)	• Includes PPPs and industry-led infrastructure upgrades but excludes private ITIs • Lacks credit-linked progression to higher education

Thus, despite renewed attention to employment outcomes, the current approach remains fragmented. Incentives for hiring and infrastructure upgrades are necessary but insufficient to align with VET policy directions needed for India.

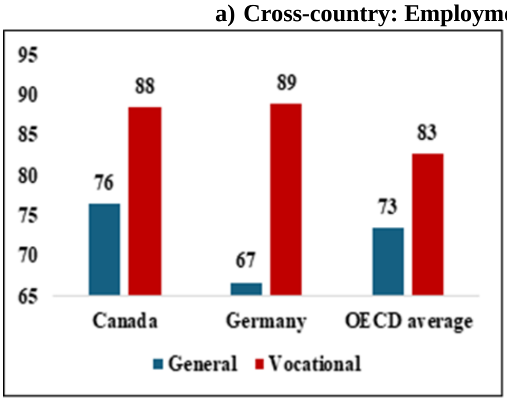
Box B3

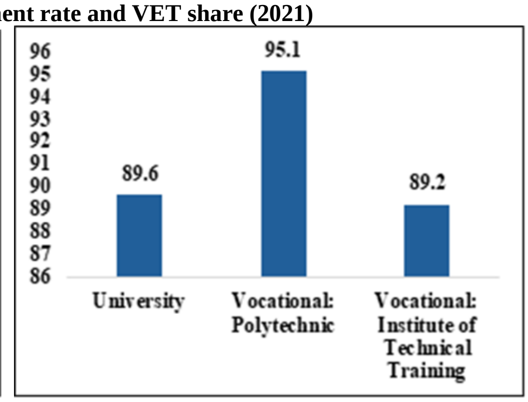
VET and Labour Market Outcomes: International Experience

Figure B3.1: VET and employment outcomes



a) Cross-country: Employment rate and VET share (2021)





b) OECD: Employment rate by general vs vocational track

c) Singapore: Employment rate by vocational and non-vocational tracks

Cross country patterns show that countries with a higher share of VET adults tend to have higher employment rates, as shown in Panel A of Figure B3.1. Notably, countries where VET is concentrated at the upper secondary level lie above the fitted line. This indicates that vocational training integrated into early school education tends may yield better labour market outcomes. For example, Germany, which introduced VET in higher-secondary schooling, combines high VET participation with high employment rates and lies above the fitted line. Canada, which introduces VET at the post-secondary or tertiary level shows high VET participation, but with lower employment rates.

However, overall, VET participation is linked with higher employment rates. Panels B and C of Figure B3.1 present within-country comparisons and confirm that vocational tracks are significantly increase the probability of employment relative to general education tracks**.** In both Germany and Canada, vocational graduates fare better than those with general education (Panel B). In Singapore too, a non-OECD country, vocational graduates have employment rates comparable to or exceeding university graduates, reflecting strong labour market alignment of vocational training (Panel C).

India should learn from international experiences and overhaul its VET programme. First, VET should be integrated into early schooling. Second, it is important to ensure nationally recognised certification of training that allows for portability of certification across education systems. Third, to improve training quality, VET courses should be aligned with local industry demand through regular market assessments, instructor recruitment should be expanded to address capacity gaps, and ITI grading should be strengthened by incorporating trainee feedback. Fourth, public-private partnerships should be encouraged by leveraging public infrastructure and private expertise. Fifth, public spending on VET should be increased and the financial viability of institutions should be ensured by linking public funding to their performance and granting them autonomy to generate their own revenue.

Chapter 4
Fostering Entrepreneurship for Job Creation

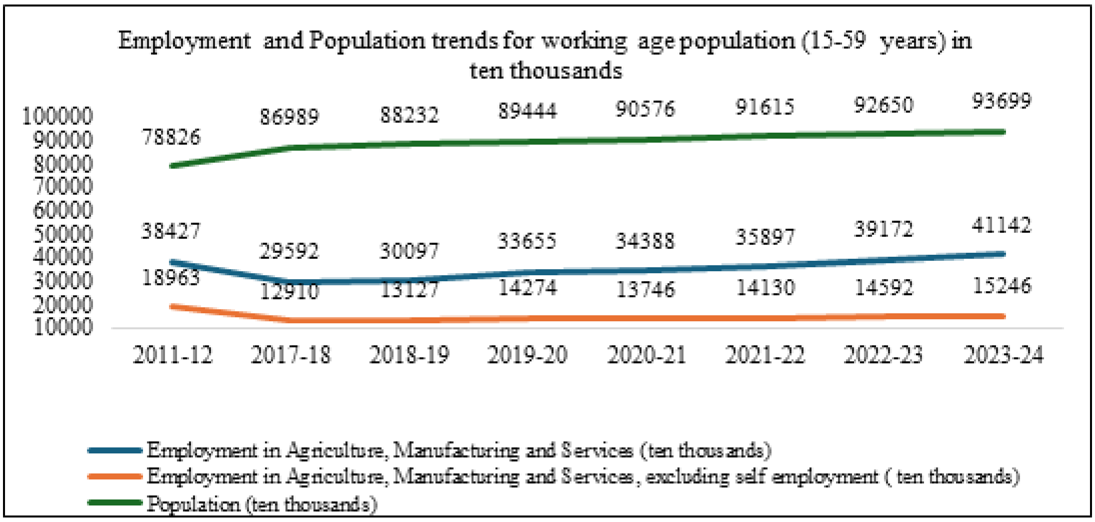
In India, much of the focus around employment generation has traditionally centred on creating more jobs. However, the largest share of the labour force is engaged in low-productivity, self-employment in terms of running establishments that are often run within household enterprises and have very low productivity.

The unincorporated or informal establishments play a crucial role in the Indian economy, absorbing a significant portion of the workforce and providing employment opportunities to a diverse population, including individuals from rural areas and those with limited formal education. It also makes substantial contributions to the country's GDP. Additionally, the sector supports the incorporated sector by acting as suppliers and service providers, forming an integral part of the domestic value chain.

4.1. Overall Trends in Employment

The increase in employment for the working age population (15 to 59 years) in India over the last few years is largely due to increase in self-employment. Figure 4.1 shows that the gap between population and employment has increased when we exclude self-employment. The growth in total employment is substantially higher than growth in employment excluding self-employment for most years.

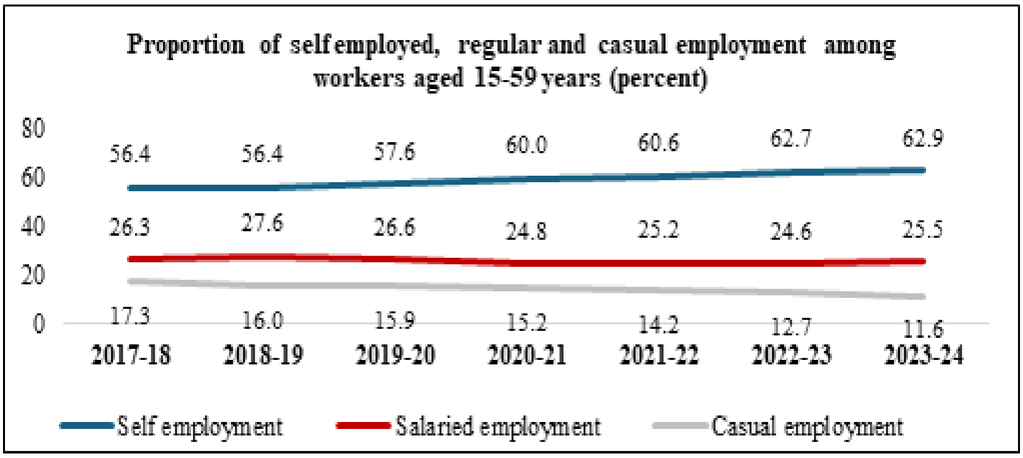
Figure 4.1: Trends and growth in employment and working-age population (15–59 years)



Source: NSS (2011-12) and PLFS (2017-18 to 2023-24); Population data is from World Bank database and 2023-24 numbers are projected numbers.
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. Employment in agriculture, manufacturing, and services is based on the Usual Status (Principal and Subsidiary) as defined in the PLFS.

There has been an overall increase in the proportion of self-employed workers and a decline in the proportion of casual and regular/salaried employment. This increase in self-employment and decrease in regular salaried employment has been more pronounced among females.

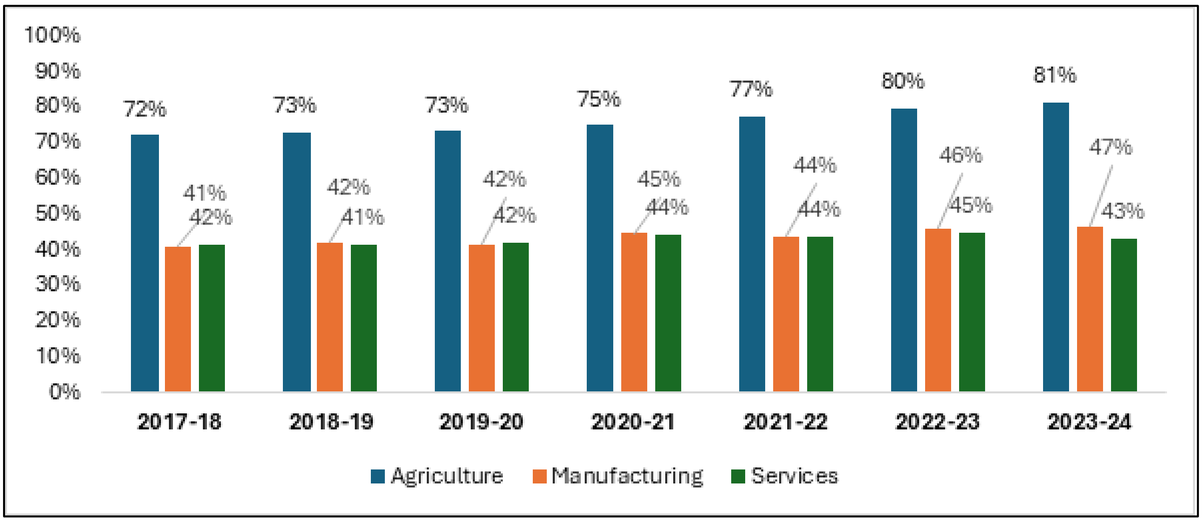
Figure 4.2: Proportion of self-employed, salaried and casual workers for working-age population (15–59 years) by gender (in per cent)



Source: PLFS (2017-18 to 2023-24).
Note: i. Self-employment includes worker engaged as an own account worker, unpaid family worker, or as an employer.

At the sectoral level, there has been an increase in the proportion of self-employed workers across agriculture, manufacturing, and services. However, most of the increase has come from self-employment in agriculture, which rose from 72 per cent in 2017-18 to 81 per cent in 2023-24.

Figure 4.3: Proportion of self-employed workers for working-age population (15–59 years) within agriculture, manufacturing and services (in per cent)

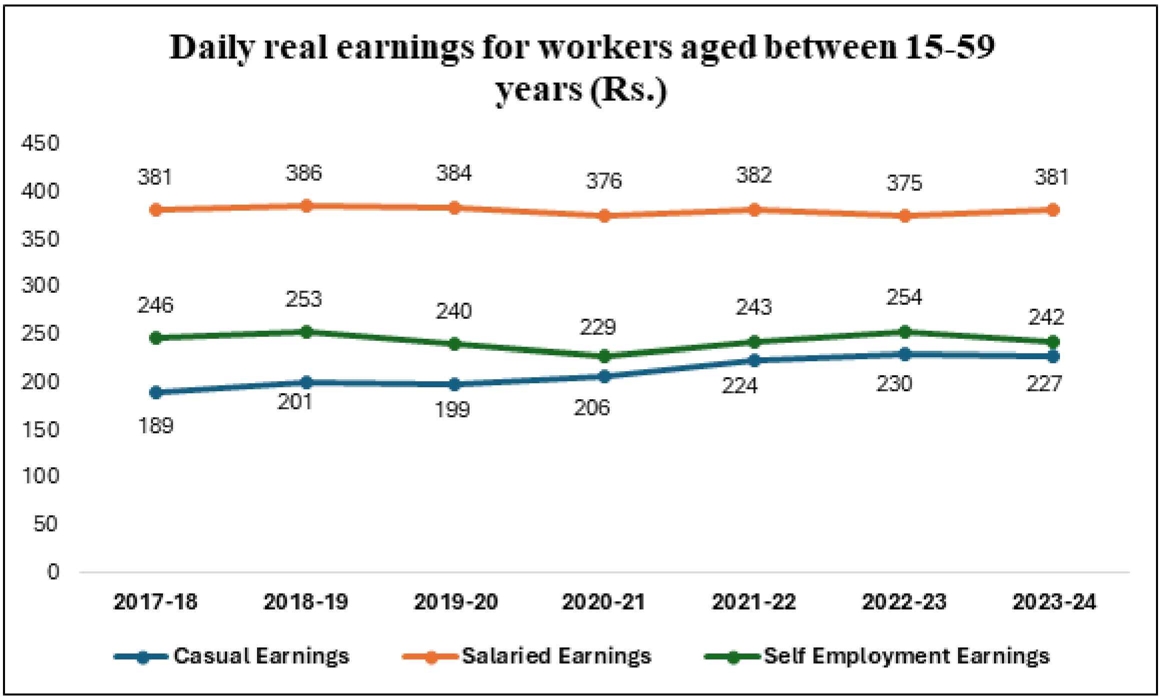


Source: PLFS (2017-18 to 2023-24).
Note: i. Self-employment includes worker engaged as an own account worker, unpaid family worker or as an employer.

4.1.1. Quality of employment in India

In addition to studying trends in self-employment, real earnings over time are examined to assess the quality of employment in India. Figure 4.4 shows that real earnings have not increased substantially over time. While the share of self-employed workers has risen, earnings from self-employment have remained largely stagnant. Notably, though most of the increase in self-employment is among women, their real earnings from self-employment have declined. Earnings from regular salaried work remained largely constant between 2017–18 and 2023–24. Disaggregating this data by gender shows that regular salaried earnings increased marginally for male workers but declined for female workers. Casual earnings increased marginally for both genders.

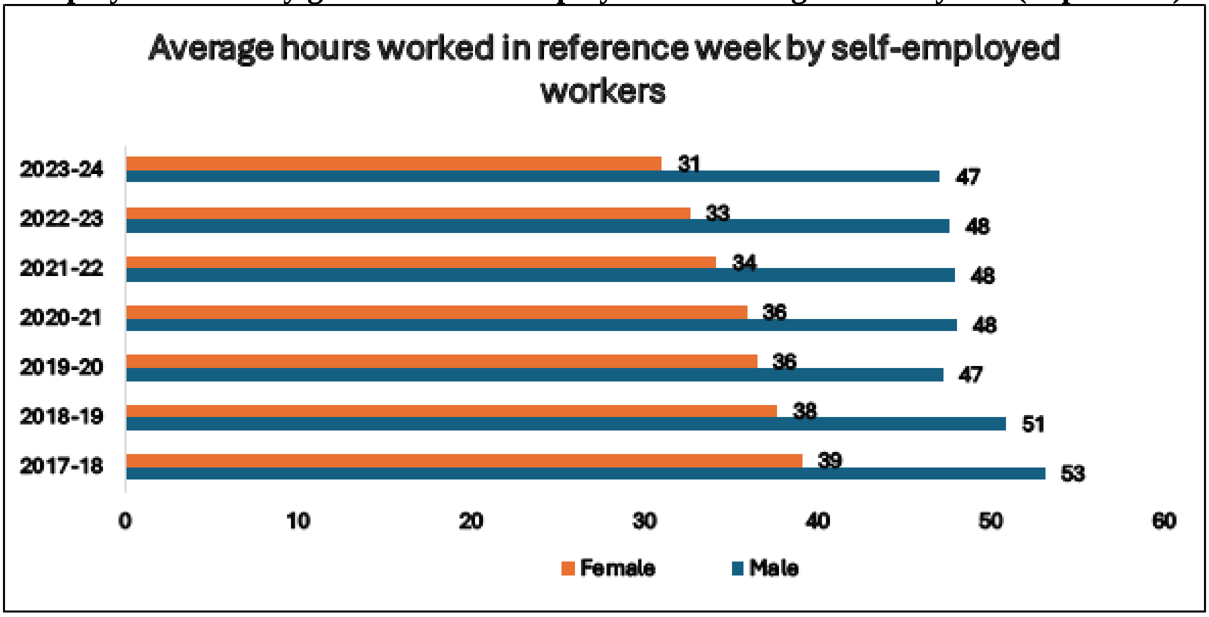
Figure 4.4: Daily real earnings in rupees from self-employment, regular, and casual work for workers aged 15–59 years



Source: PLFS (2017-18 to 2023-24).
Note: i. Nominal earnings are deflated using the combined Consumer Price Index (CPI) for rural and urban areas (base year = 2012); ii. Casual workers exclude those engaged in public works; iii. Average earnings are calculated based only on workers who report positive incomes.

Another indicator of the quality of employment is the under-employment rate. Figure 4.5 shows that the average number of hours worked per week by male workers is around 47, while for female workers, it is only about 31 hours. This translates to an average of approximately 6.7 hours per day for men and 4.4 hours per day for women, assuming a seven-day reference week, as followed in the PLFS. Additionally, more than 3 per cent of all self-employed workers are under-employed, indicating a mismatch between the willingness to work and available work.

Figure 4.5: Average hours worked in a seven-day reference week and under-employment rate by gender for self-employed workers aged 15–59 years (in per cent)



Source: PLFS (2017-18 to 2023-24).
Note: i. Self-employed workers are identified based on the Current Weekly Status (CWS) with codes 11, 12, 21, 61, and 62; using the seven-day reference week; ii. Total hours worked are calculated by summing the number of hours worked by self-employed workers on each of these seven days, and average daily hours are computed by dividing the total by 7.

4.2. Unincorporated Non-agricultural Enterprises

Unincorporated non-agricultural enterprises provided livelihood to more than 12 crore workers in India in 2023-24. An overwhelming majority of these workers are self-employed or entrepreneurs running micro, small, and medium enterprises. In this section, we analyse the Annual Survey of Unincorporated Enterprises (ASUES) data and explore the pathways for growth of these enterprises recognising that boosting productivity of business establishments is vital for expanding employment opportunities.

Table 4.1 describes the trends in these enterprises characteristics since 2021 using the ASUES Surveys.

Table 4.1: Descriptive statistics – ASUSE 2021-22 to 2023-24

Variable	2021-22	2022-23	2023-24
Total number of enterprises (in Crores)	6.0	6.5	7.7
Type of Enterprise (%)			
HWE	14.2	14.9	13.0
OAE	85.8	85.1	87.0
Industry (%)			
Manufacturing	28.9	27.4	26.1
Services	71.1	72.6	73.9
Region (%)			
Rural	55.6	54.8	52.2
Urban	44.4	45.2	47.8
Type of Ownership (%)			
proprietary (male)	72.3	71.8	69.1

proprietary (female)	22.8	22.9	25.8
partnership between members from the same household	0.6	0.3	0.2
partnership between members not all from the same household	0.5	0.4	0.5
Self Help Group	3.1	3.7	3.5
Society/Trust/Club/etc.	0.5	0.8	0.7
Co-operative	0.1	0.1	0.1
Highest level of education for proprietor (%)			
Illiterate	7.7	6.6	6.4
Below Primary	13.2	11.2	10.9
primary and above	30.6	29.0	28.3
secondary and above	23.2	24.4	24.4
higher secondary and above	13.2	14.4	15.2
graduate and above	12.1	14.4	14.9
Technical /vocational training of proprietor (%)			
Yes	8.2	9.3	8.6
No	91.8	90.7	91.4
Number of years of operation of the establishment (%)			
less than one year	4.8	4.8	4.1
one to three years	17.6	15.7	15.8
more than three years	76.4	79.5	80.0
not known	1.2	0.0	0.0
Location of the establishment (%)			
within household premises	42.0	40.8	40.8
with fixed premises and with permanent structure	39.7	39.2	37.2
with fixed premises and with temporary structure/ kiosk/ stall	2.3	2.2	2.1
with fixed premises but without any structure	1.5	2.2	2.7
mobile market	2.1	2.3	2.2
without fixed premises (street vendors, etc.)	12.4	13.3	15.1
Nature of operation (%)			
perennial	98.9	99.0	99.1
seasonal	1.0	0.9	0.9
casual	0.2	0.1	0.0
Used computer (%)			
Yes	5.5	6.1	5.5
No	94.5	93.9	94.5
Used Internet (%)			
Yes	13.9	21.1	26.2
No	86.1	78.9	73.8
Enterprises with loan outstanding (%)			
Total Enterprises with loans	11.0	12.1	10.2
Total Enterprises without loans	89.0	87.9	89.8

Source: ASUSE 2021-22 to 2023-24.

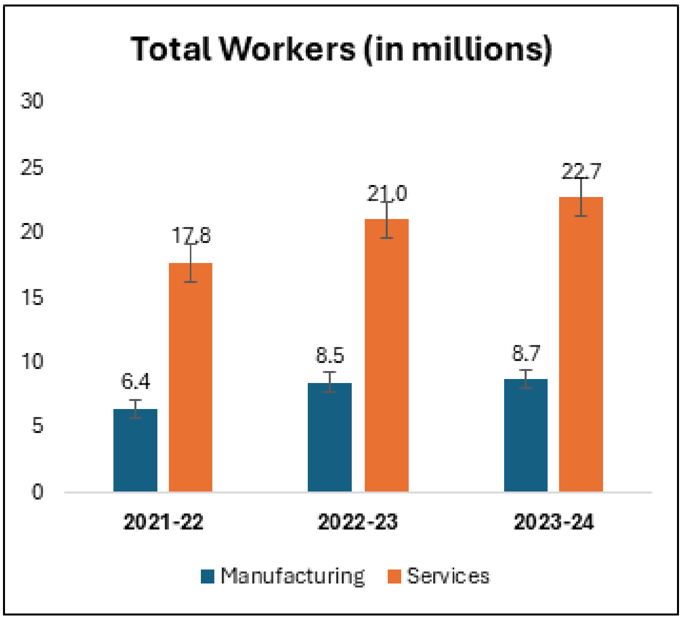
OAEs dominate the landscape, and in the services sector (Table 4.1). OAEs do not hire any workers, while the average for HWEs is about 10 workers and the number of workers hired per HWE has been increasing over the years. The GVA of HWEs is almost 7.5 times of OAEs, as shown in Table 4.2.

Table 4.2: Summary statistics on employment and productivity (ASUSE)

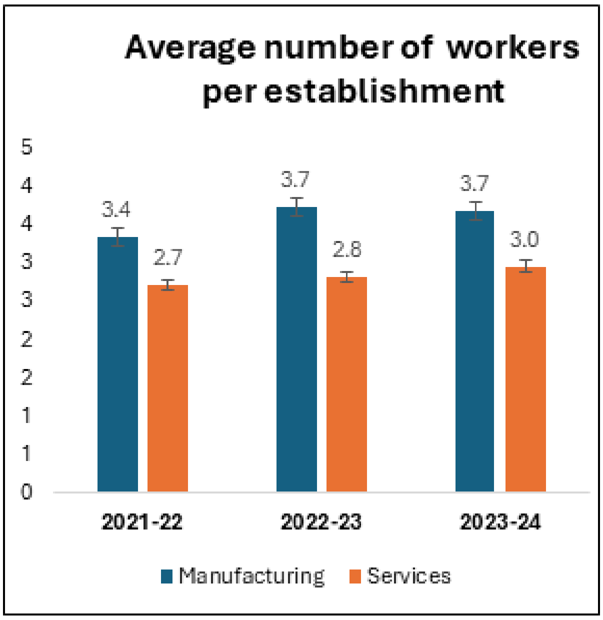
	2021-22	2022-23	2023-24
Total number of hired workers (in crores)[1]			
Manufacturing	2.8	3.1	3.4
Services	7.0	7.9	9.1
Total	9.8	11.0	12.4
Average number of hired workers in per HWE			
Manufacturing	3.4	3.7	3.7
Services	2.7	2.8	3.0
Annual (real) emolument per hired worker (Rs)			
Manufacturing	66754.8	68487.0	71686.6
Services	80803.9	75679.4	76147.3
Gross Value Added			
Number of enterprises with and without reported GVA (In '000)			
No	248.6	287.0	246.3
Yes	59454.0	64761.4	76889.3
Annual (real) GVA per establishment-by-establishment type (Rs)			
HWE	519706.4	521409.3	540972.1
OAE	72292.5	74925.1	69312.4
Annual (real) GVA per establishment (Rs)			
Manufacturing	98166.5	119296.5	100321.7
Services	153693.8	148457.4	136408.4

Source: ASUSE 2021-22 to 2023-24.
Note: i**.** Services sector includes trade; ii. Real GVA calculated at 2011-12 prices, iii. ASUSE calculates GVA only for market establishments. Therefore, in the pooled data, there are some enterprises with no reported GVA amount. However, their proportion is negligible: 0.42 per cent in 2021–22, 0.44 per cent in 2022–23, and 0.32 per cent in 2023–24.

Figure 4.6: Hired workers by sector and per establishment



(a) Total by sector



(b) Per establishment sector

Source: ASUSE 2021-22 to 2023-24.
Note: Services sector includes trade.

Data show that the unincorporated services sector employs a significantly higher number of workers as compared to the unincorporated manufacturing sector. This gap has decreased slightly over a period of time (Figure 4.6a), but the number of workers hired per establishment is higher in manufacturing than services (Figure 4.6b).

Table 4.3: Employment elasticity by sector (ASUSE)

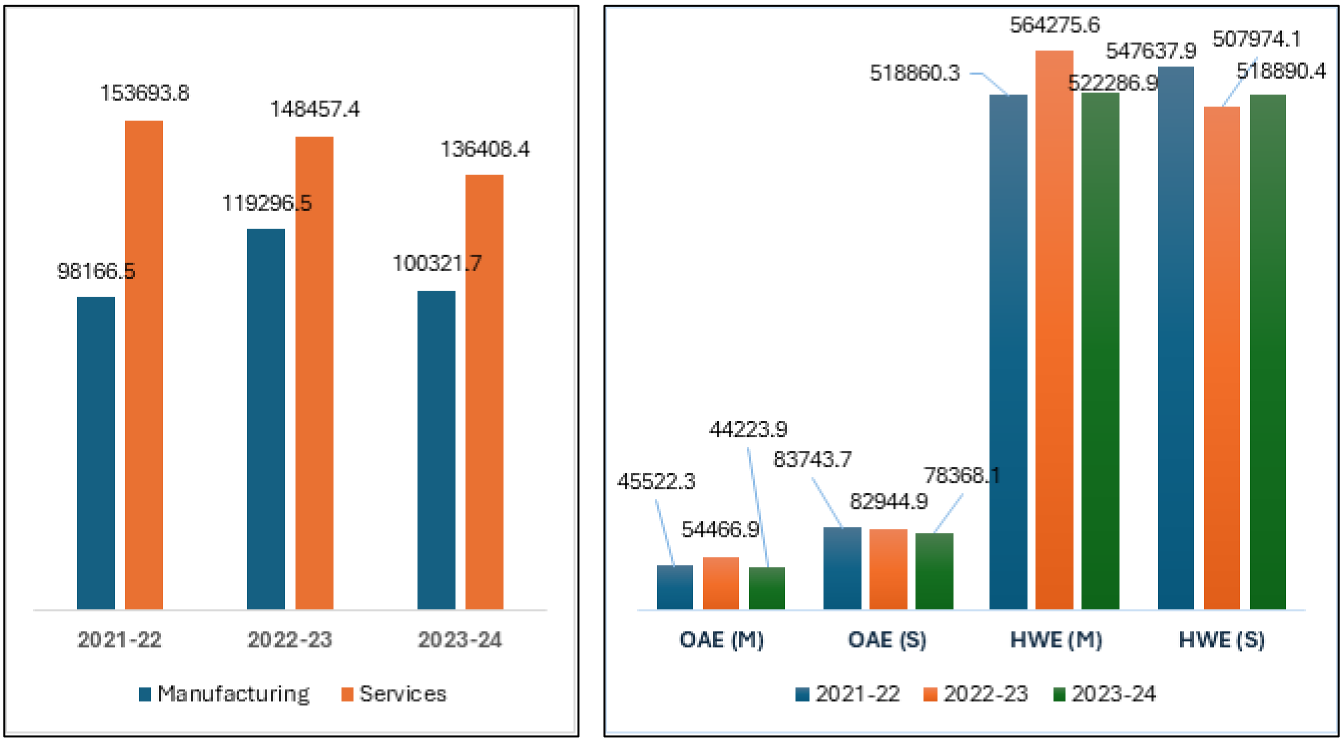
Sector	GVA Growth (%)	Employment Growth (%)	Employment Elasticity
2022-23			
Manufacturing	25.6	32.0	1.2
Services	7.4	18.4	2.5
2023-24			
Manufacturing	-5.0	2.7	-0.5
Services	11.1	8.1	0.7

Source: ASUSE 2021-22 to 2023-24.
Note: i**.** Services sector includes trade; ii. Real GVA calculated at 2011-12 prices.

In 2022-23, employment elasticity in the services sector was twice that of manufacturing, as shown in Table 4.3. For every 1 per cent increase in service sector output, employment grew by 2.5 per cent, whereas in manufacturing, employment increased by 1.2 per cent for the same output growth.

However, the trend shifted significantly in 2023-24. Despite a 5 per cent decline in GVA, manufacturing employment still grew by 2.7 per cent, suggesting labour retention even in an economic slowdown. In contrast, services saw an 11 per cent GVA increase, but employment grew by only 8.1 per cent, indicating a shift toward capital-intensive growth where output expansion is driven more by technology and productivity improvements rather than labour hiring.

Figure 4.7: Annual (real) GVA per establishment (in Rs) in manufacturing and services

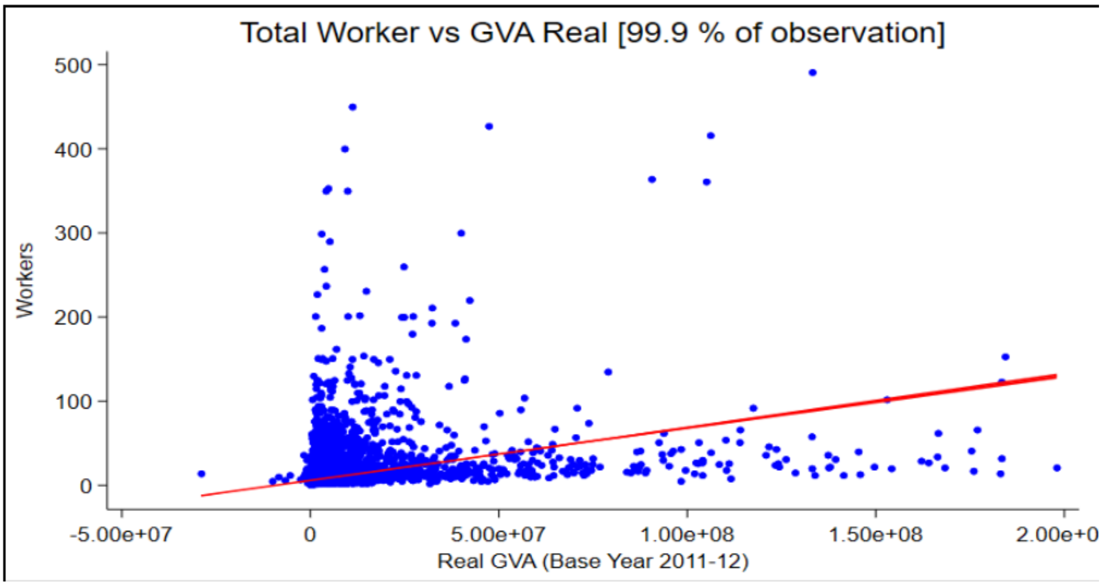


(a) **By sector** **(b) By sector and establishment type**

Source: ASUSE 2021-22 to 2023-24.
Note: i. Services sector includes trade; ii. Real GVA calculated at 2011-12 prices; M–manufacturing, S—services.

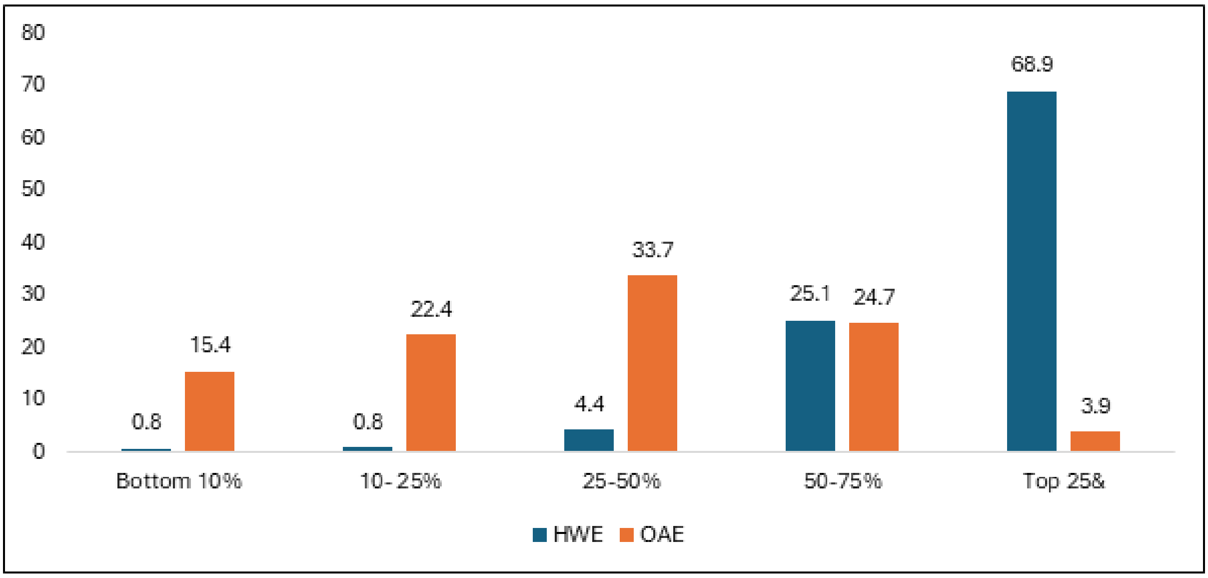
The descriptive statistics above indicate that increasing the productivity of these establishments are critical to shift them from OAE to HWEs and thereby creating more jobs while fostering productive entrepreneurship (correlation coefficient 0.346 (p-value <0.01)).

Figure 4.8: Correlation between hired workers and GVA (2022 – 24)



Source: ASUSE 2021-22 to 2023-24.
Note*:* i. Applies an upper limit of Rs 200,000,000 (Rs 20 crores) on GVA and 500 on Total Workers. This restriction helps focus on the core distribution, excluding extreme outliers that obscure general patterns; ii. Sample size: 47,046 total observations; iii. Used in Graph: 47,017 observations (99.9 per cent of the total).

Figure 4.9: Distribution of GVA by type of enterprise (2022-24)

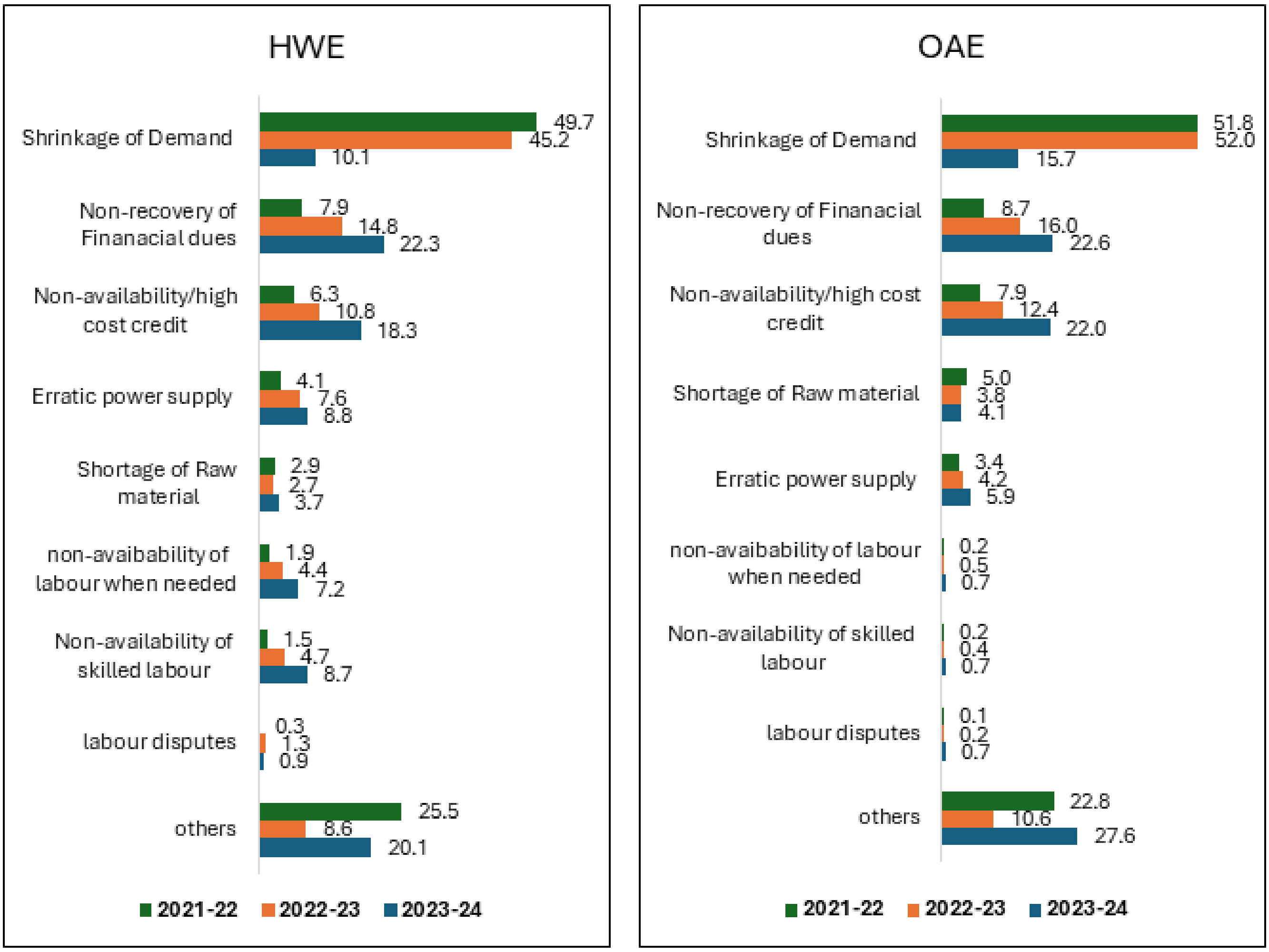


Source: ASUSE 2021-22 to 2023-24.

4.2.1. What ails enterprise growth?

We summarise the data on issues faced by these enterprises in its operation in the last 365 days below. Non-availability of credit and non-payment of financial dues are the two main constraints reported by both HWEs and OAEs in recent years.

Figure 4.10: Problems faced by HWEs and OAEs in their operation during the last 365 days



Source: ASUSE 2021-22 to 2023-24.
Note: The figure is based on the problems faced by the establishment in its operation in the last 365 days, as reported by the respondents. The "Others" category is not defined in the dataset.

4.2.2. Factors affecting growth of enterprises

We analyse the pooled cross-sectional data from the ASUSE surveys for the years 2021–22 to 2023–24. The sample is restricted to enterprises that reported at least one worker and have reported some information about the loan, which gives us a sample of 156,630 enterprises.

We conduct separate analysis at the 10th (small business), 50th (medium business), and 90th percentiles (large business) of the GVA distribution to capture the heterogeneous effects of various enterprise characteristics across the GVA distribution. We use real GVA as a proxy for enterprise productivity and growth potential to identify the key drivers of higher GVA (such as access to credit, technology adoption, proprietor education, and industry characteristics). The analysis provides insights into the factors that can enable the low GVA OAEs to enhance their productivity and earnings. Such improvements are critical prerequisites for the transition from OAEs to high GVA, HWEs, thus promoting both employment generation and economic upgrading.

To illustrate the impact of two key enablers—access to formal credit and technology adoption—we present separate sections analysing each factor. In both cases, we use GVA as the primary outcome indicator. The graphs in each section are developed using a two-step approach:

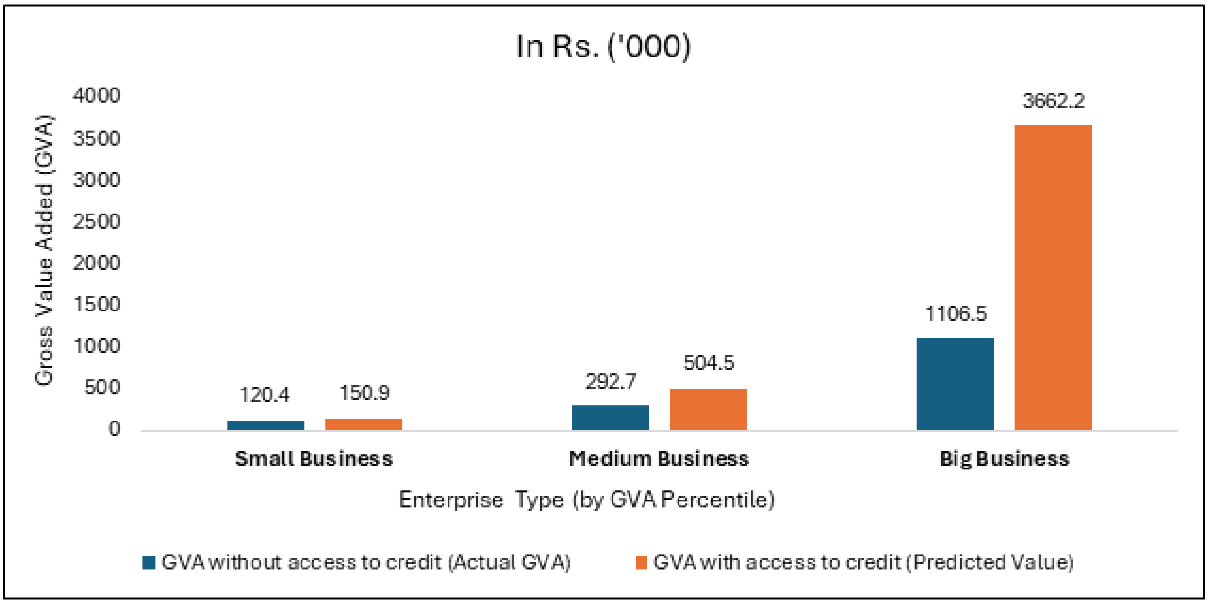
1. *Actual GVA* values are plotted for enterprises *without* access to credit or technology, based on ASUSE survey data.
2. *Predicted GVA* values are then computed for enterprises with access to credit or technology using the coefficients obtained from the above quantile regression models for different enterprise sizes (small, medium, and large). These predicted values represent the potential GVA that otherwise similar enterprises (in terms of proprietor education, training, and sector, etc.) could achieve if they had access to these enablers. (Refer to Annexure Table A4.4 for detailed regression specifications and prediction methodology.)

   These numbers were plotted as charts to visually show how access to credit increases GVA in the following section:

A. Access to Formal Credit

Unincorporated enterprises, which form a significant component of the informal sector, typically operate without formal legal status and are often owned and managed by individuals or families (ILO, 1993). Their informal nature presents a range of structural challenges that constrain both firm growth and productivity. Chief among these is limited access to credit, which restricts capital investment and prevents these firms from achieving efficient scales of production. This persistent undercapitalisation, when coupled with low educational attainment among workers, results in low productivity and severely hampers their potential for expansion and competitiveness (ILO, 2018).

Figure 4.11: Impact of access to institutional credit across business sizes (in Rs. '000)



Source: ASUSE 2021-22 to 2023-24.
Note*:* Actual GVA refers to the Gross Value Added (GVA) of enterprises without access to institutional credit, calculated using ASUSE data. Predicted GVA represents the estimated GVA for enterprises with access to institutional credit, derived from a quintile regression model where the dependent variable was the GVA of enterprises. Small, medium, and big businesses correspond to the 10^{th}, 50^{th}, and 90^{th} percentiles of the GVA distribution, respectively. Predicted GVA values for enterprises with access to credit were calculated using the intercept and coefficient from the model: Predicted GVA=Intercept + Coefficient

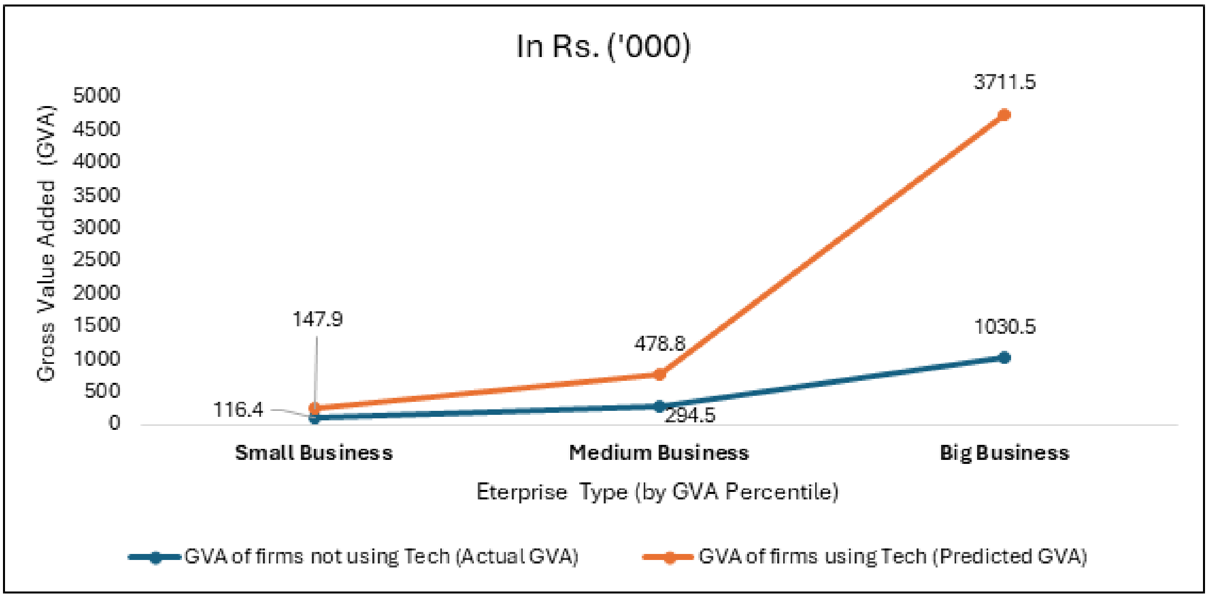
Figure 4.11 highlights that access to formal credit significantly enhances enterprise-level productivity, i.e., GVA. While small businesses see only a marginal gain in GVA (from Rs 1.2

lakhs to 1.51 lakhs), medium and large businesses experience substantial boosts—from Rs 2.93 lakhs to Rs 5.04 lakhs and Rs 11.07 lakhs to Rs 36.62 lakhs, respectively.

This pattern aligns with findings in the literature (e.g., Bianchi and Milo, 2012), where credit constraints disproportionately affect high-potential entrepreneurs, particularly those capable of scaling operations. Larger businesses are better able to translate access to credit into productivity gains due to their better infrastructure, market access, and capacity to invest in growth-enhancing inputs like technology and skilled labour. Medium-sized firms also benefit meaningfully from credit, showing a near doubling of their GVA. This indicates strong latent potential in the mid-tier segment that can be unlocked with greater access to credit. In contrast, small businesses show more modest improvements, suggesting that while credit helps, it must be complemented with other forms of support such as capacity building, market linkages, and business development services to meaningfully impact productivity.

B. Technology Adoption

Figure 4.12: GVA of firms using and not using technology across business sizes (in Rs '000)



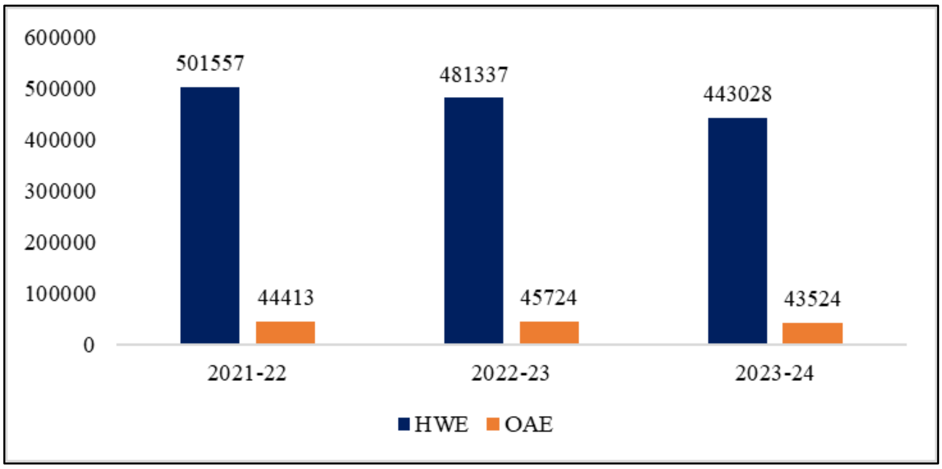
Source: ASUSE 2021-22 to 2023-24.
Note: ibid.

A firm is considered to be "using ICT technology" if it has used either a computer, the internet, or both during the last 365 days. Figure 4.12 shows that the adoption of technology leads to increase in GVA for firms of all sizes. However, the impact of technology is more pronounced for larger firms, perhaps due to access to better technology as well as higher capacity to leverage the benefits of tech.

B4 Box Case Study: Technology adoption for women's entrepreneurship

The increase in the share of self-employed women in urban India of 8 pp points between 2017-18 and 2022-23 (PLFS, 2017-18 and 2022-23), has been accompanied by a rise in the proportion of micro-enterprises owned by women from 20 to 26 per cent in the same period. Over 93 per cent of these are own-account enterprises (ASUSE data, 2022, 2023 and 2024), while the GVA of women-owned HWEs declined from Rs 501,557 to Rs 443,208 (in 2011-12 prices) (see Figure B4.1).

Figure B4.1: Annual real GVA per establishment of women-owned urban enterprises by establishment type



Source: ASUSE 2021-22 to 2023-24.
Note: Real GVA calculated at 2011-12 prices.

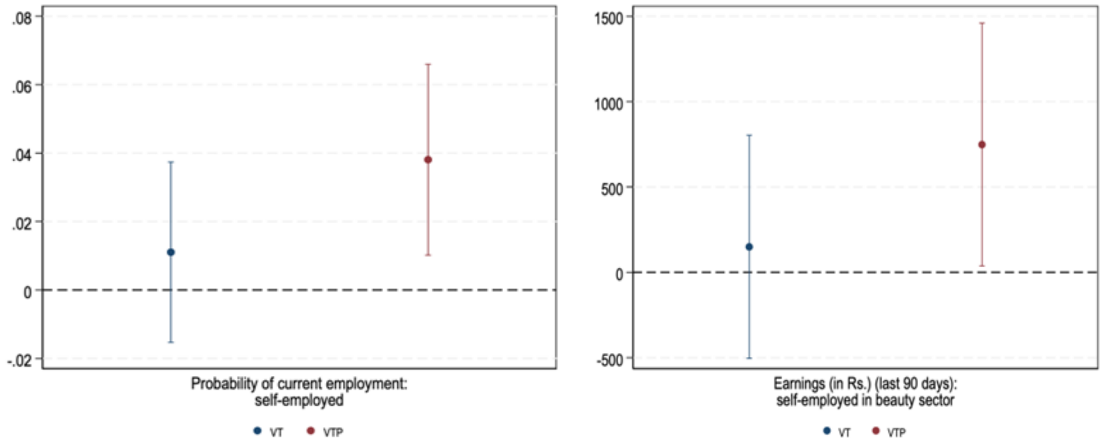
Lack of skills is shown to be an important constraint facing women entrepreneurship in India (Field et al., 2010) along with access to capital (Carranza and Carranza, 2018). Recent qualitative evidence suggests that digital skills can be a high-leverage area when paired with market relevant curricula (UNESCO, 2018) for entrepreneurship. While 55% of adult men have ever used the internet, only 33% of women ever have (NFHS 2019). Importantly, only 30% of India's social-media users are female (Global Digital Report, 2024), suggesting that limited digital skills constrain women's ability to leverage social media for commercial purposes.

Afridi, Gupta, Heath and Mahajan (2025) design and evaluate vocational training for almost 2000 women by implementing an individual-level randomised intervention in Delhi and Bengaluru that includes a control group and two treatments: vocational training (VT) focused on sector-specific hard skills with on-the-job training (total duration of five months) and VT with an additional Project-Based Experiential Learning (PBEL) component of two weeks that focuses on digital skills and basic soft-skills required for the sector (VTP).

Almost a year following the start of training, they find that women assigned to the VTP arm are more likely to be currently employed than those assigned to the VT. The higher probability of current employment of VTP women is driven by a 3.8 pp increase in their likelihood of being self-employed, accompanied by higher earnings in self-employment (see Figure B4.2). Women in VTP group worked 17 hours more and earned INR 1070 more in the previous three months. These labour market impacts are accompanied by a significant increase of 7.5 pp in the usage of social media for business purposes by women in the VTP arm relative to women in both the control and the VT groups.

This suggests that new age digital skills, combined with hard and soft skills, can enable women to engage in entrepreneurial activities that are more remunerative, while at the same time allowing greater flexibility of work.

Figure B4.2: Impact of digital skills on self-employment and earnings



Source*:* Afridi et al. (2025).
Note*:* Panel A on the left hand shows the probability of being self-employed and Panel B on the right hand shows marginal effect on earnings of VT and VTP vocational training. 90 per cent confidence bands.

C. Growth in GVA and its Link to Employment Expansion

The preceding sections showed that access to credit and technology adoption significantly raise the productivity of enterprises, especially among medium and large firms. But higher productivity alone is not the end goal—what matters equally is whether this growth translates into more jobs. To understand this link, we analyse how increases in GVA relate to enterprise expansion in terms of employment.

We find a strong and positive relationship between GVA and the number of hired workers. Enterprises with higher GVA are significantly more likely to employ more workers, underlining the role of productivity growth as a pathway to job creation. Our analysis shows that a 10 per cent increase in GVA is associated with an approximately 4.5 per cent increase in the number of hired workers, holding other factors constant (Refer to Annexure Table A4.5 for more details on OLS regression estimates.)

To understand this relationship in simple terms, consider a medium-sized enterprise whose GVA increases from Rs 2.93 lakhs to Rs 5.04 lakhs due to improved access to formal credit—representing a 72 per cent rise in GVA. Based on the estimated elasticity, where a 10 per cent increase in GVA leads to a 4.5 per cent increase in the number of hired workers, this 72 per cent increase in GVA would correspond to an approximately 32.4 per cent increase in employment. In practical terms, if the enterprise initially employed 10 workers, this productivity gain could enable it to hire 3-4 additional workers, increasing total employment to about 13 or 14 workers. This example highlights how enhancing enterprise productivity—through better credit access or similar support—can lead to meaningful employment generation.

Summary

The informal enterprise data analysis shows that while the incidence of self-employment is high in India, the overwhelming majority of the self-employed are 'subsistence' entrepreneurs – they operate with low capital and do not hire labour. We find a strong correlation between an enterprise's GVA and the probability that it hires workers and thereby generates employment. Two critical constraints to the growth of these enterprises are access to credit and technology. Access to institutional credit and digital technologies can almost double the size of these informal medium enterprises. A 10 per cent increase in GVA of these informal enterprises can raise employment by almost 5 per cent.

Chapter 5
Policy Implications

Our projections of the number of jobs that can be created through output growth in the labour-intensive manufacturing and services sub-sectors between 2025 and 2030, using different growth scenarios, indicate that inter-sectoral linkages can have a multiplicative effect on employment in the aggregate economy, increasing employment by up to 200 per cent relative to existing scenarios. 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 per cent increase in employment in the labour-intensive sectors by 2030.

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

We underline the need for a multi-pronged approach to increase investment and production capacity in labour intensive manufacturing and services sectors:

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

- *Policy incentives to stimulate foreign and domestic investments in manufacturing and services sectors:* The Central Government has recently introduced the new version of the PLI scheme. However, the Production-Linked Incentive (PLI) scheme is primarily focused on expanding production of high value products with backward-linkages, which require high-skilled, specialised labour and are relatively less focused on low and middle-skilled labour- intensive sectors. Specifically, over 50 per cent of the PLI budget is allocated for large-scale electronics, IT hardware, and drone manufacturing. However, the highest number of jobs under the scheme has been created in the food processing and pharmaceutical industry. Hence there is a mis-match between the weight of the budgetary allocation and the potential for employment creation.

  Cases in point are textiles and footwear industries that have high labour intensity but lower exports than India's potential, particularly in the context of new global headwinds (see box B5.1). In the services sector, hotels and tourism have seen slow growth in the number of foreign visitors and particularly poor recovery post pandemic. Here again, a policy-driven focus on attracting both foreign tourists and domestic tourists is required. In addition, the opportunities in the labour-intensive education sector remain untapped, given the demand stemming from the size of India's youth population, and the tightening of student immigration policies in the West.

- *Loosen labour regulations:* Data show a persistent and steady decline in the labour intensity of production technology across sectors. This deepening of the capital intensity of the production process, particularly in and including labour-intensive manufacturing and services industries, is likely to continue and fasten with the advent of AI. We cannot ignore the long-standing issue of loosening our labour regulations that artificially inflate the cost of labour and encourage the adoption of capital-intensive technologies. Our analysis suggests that within the formal/registered manufacturing sector, employment elasticities may have increased, in contrast to the observed decline in employment elasticity for the manufacturing sector as a whole. One possible explanation for this is the increased hiring of contract labour to circumvent labour regulations. This underlines the need to allow more flexible hiring practices. The onus of adopting flexible labour policies, however, lies with the state governments.
- *Credit expansion and ease of doing business*: Lower formal interest rates can increase credit take-up but only if businesses anticipate demand for their products. Our analysis of the ASUSE data on unincorporated non-agricultural establishments shows that access to credit can lead to significant increase in the GVA of an enterprise and thereby the size of the firm and its capacity to hire workers. At the same time, ease of registering and conducting business can significantly enhance value-added and thereby hiring.

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

However, to meet the Economic Survey's goal of almost 8 million annual non-farm jobs, a rapid expansion of the formally trained workforce is essential. Additionally, the Future of Jobs Report 2025 highlights that 63 per cent of India's workforce will need re-skilling or up-skilling 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 programmes are tailored to meet specific industry needs. Incorporating soft skills, digital literacy, and Information and Communication Technology (ICT) skills into training programmes can further enhance employability, particularly within these service sub-sectors. The poor outcomes of training in India stem from a combination of low formal training rates, misalignment of curricula with industry needs, lack of standardisation, and the short-term nature of training programmes.

Policy initiatives so far have either tinkered at the margins of the education system or been introduced as afterthoughts. They are unlikely to transform workforce productivity and employability without a fundamental overhaul of a system that is already outdated in a world where both workplaces and work itself are changing rapidly. We recommend a systemic overhaul of vocational training, as follows:

1. *Integrate VET into early schooling:* Countries that introduce VET earlier in the schooling system show a stronger association with better labour market outcomes. In Germany, for example, VET is integrated at the upper secondary level through a dual

system combining school education with paid apprenticeships. Germany has an even higher employment rate of trainees compared to Canada, where VET courses are integrated with post-secondary or tertiary education. In contrast, in India, VET is an after-thought—offered post high school education, which not only shortens the period available for hands-on training before the youth enter the job market, but also does not allow for orientation of leaning towards employable skills. The National Education Policy (NEP) 2020 recommends integration with early school education, but progress in this direction has been slow.

2. *Define pathways to higher education:* The existence of defined pathways to higher education or skill portability is important even if VET is embedded in the later stages of education. For instance, Singapore offers VET at the post-secondary/non-tertiary level through a dual vocational tracks (Institute of Technical Education (ITE)), at post-secondary level + Polytechnics at tertiary level), but has defined pathways from ITE to a Polytechnic and then onto traditional University education. Canada offers tertiary-level VET via community colleges and polytechnics, with work credentials recognised as part of evaluation to enable smooth transitions to higher education. India, in contrast, offers no formal academic progression from VET to mainstream higher education neither does our education system offer credit transfers between systems. This reduces the uptake of VET by many who wish to keep the option of traditional, academic education viable. To address this, fast-track reforms are needed to implement the National Credit Framework, which defines clear progression pathways and aims to establish a board for nationally recognised certifications.

3. *Improve the perception and quality of VET training:* Singapore has industry-led curriculum design, high instructor quality, regular audits, and a mechanism that seeks constant feedback from employers and trainees. In India, in contrast, many courses are outdated and misaligned with industry needs. Over one-third of ITI instructor posts are vacant due to limited training capacity at National Skill Training Institutes (NSTIs). Quality monitoring is weak, with irregular ITI grading and no feedback systems. To improve training quality, VET courses must align with local industry demand through regular market assessments, while expanding NSTIs, fast-tracking instructor recruitment, and strengthening the ITI grading system. As per the simulation results, improving training quality, along with increasing the share of formally trained workers, can lead to higher employment gains.

4. *Strengthen public-private partnership:* In Germany, Singapore, and Canada, governments fund VET institutions while employers share training costs, support apprenticeships, and help design curricula. In India, however, employer engagement is minimal—ITIs rely heavily on government funding with little private investment, while MSMEs, though central to local job creation, have limited capacity to engage with ITIs. Sector Skill Councils (SSCs) also lack state-level presence. To address this, MSME and SSC participation must be strengthened, and CSR funding strategically leveraged to enhance industry relevance.

5. *Increase public spending on VET and ensuring the financial viability of these institutions:* India allocates around 3 per cent of total education expenditure to VET, compared to 10-13 per cent in countries like Germany, Singapore, and Canada. Public funding can be optimised if the financial viability of VET institutions is high. However, in India, the financial viability of ITIs is a concern because per-student costs are high due to seat under-utilisation and institutions having little autonomy to generate their own revenue. This can be addressed by linking public funding to performance and

granting ITIs greater autonomy to generate their own revenue, while maintaining core funding to ensure equitable access.

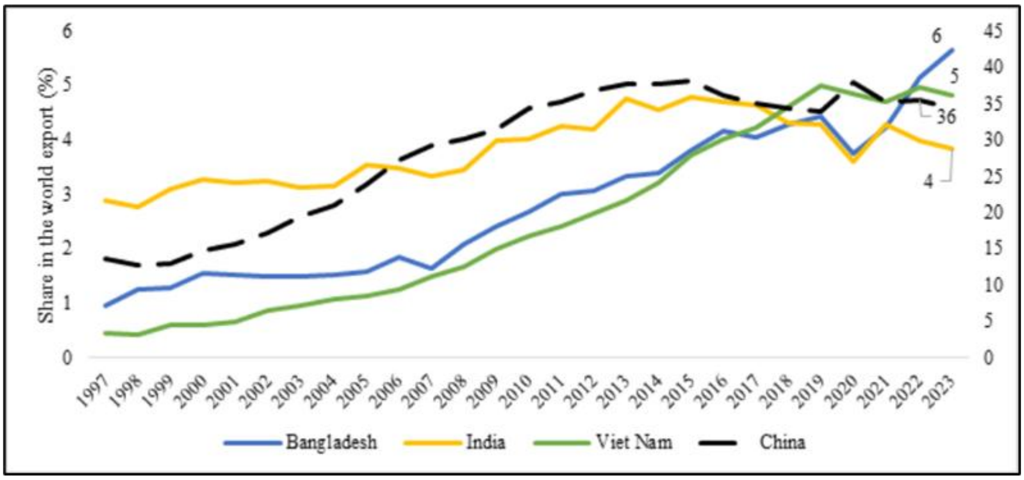
Our simulation results indicate under the “high growth” scenario, the gains from enhancing the marginal impact of training are more pronounced. The number of additional jobs rises to 14.8 million when both the share and the impact of training are increased, compared to 14.0 million when only the share is enhanced—resulting in 800,000 additional jobs. This corresponds to a 14.2 per cent increase in employment, as opposed to 13.4 per cent 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 (See Box B5.2).

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

B5.1: Improving employment opportunities in the textile and garment industry

Trends in the recent half decade show a gradual but fairly sustained shift in India’s export share of the textile market. While China continues to be the largest textile exporter, its global market share has slightly dipped since 2015. This decline has been accompanied by a notable rise in the export shares of Vietnam and Bangladesh, both of which adopted export-led industrial strategies and favourable policy environments to build strong textile sectors.

Figure B5.1: Rising export shares of Vietnam and Bangladesh versus India (1997–2023)



Source: WTO Statistics; Authors’ calculations.
Note: i. Export values have been calculated using merchandise export data (in million USD) for textiles and clothing; ii. Export shares are computed as the ratio of a country’s export value to the total world export value for the corresponding categories of textile and clothing; iii. The left-hand scale represents the share for China; iv. The right-hand scale represents the share for India, Bangladesh, and Vietnam.

In contrast, India’s share of world textile exports has declined since 2017, despite its large cotton base and full-fibre-to-fashion value chain. Much of India’s under-performance can be attributed to fragmented infrastructure, weak enforcement of labour laws, and dispersed production structure. Meanwhile, Vietnam and Bangladesh benefited from industrial clustering, targeted fiscal incentives, and trade agreements.

However, evolving global trade policy necessitates new strategies for growth of this sector, with significant implications for employment.

First, a focus on bilateral trade agreements, such as the UK-India Free Trade Agreement. This FTA eliminates tariffs on almost 99 per cent of Indian textile and apparel exports to the UK, which previously faced an 8-12 per cent import duty. Alongside regional trade agreements, new markets for textile exports outside of the US, have become an imperative.

Second, state-level industrial strategies offer valuable lessons. An apt example is Tamil Nadu, which stands out for its effective adoption of Centrally-led policies, complimented by the states' own efforts. In 2024–25, it contributed almost 22 per cent to India's total textile exports, reflecting an 11.8 per cent growth over the previous year (NIRYAT). The 2019 Tamil Nadu textile policy (soon being upgraded to 2025 Tamil Nadu textile policy) provides comprehensive support through:

Worker housing, environmental compliance support, and health and safety standards. Skill development initiatives embedded within a broader labour market strategy aimed at addressing both the skill gap and skill shortage across the organied and unorganised segments such as spinning, weaving, knitting, and technical textiles. A key initiative is the *Training of Workmen* scheme, under which 8,950 individuals are receiving vocational training (Department of Textiles, Tamil Nadu). This approach integrates targeted skilling, gender-inclusive hiring, and fostering more equitable and formal job creation.

- To move up the value chain, the State has also launched the Tamil Nadu Technical Textile Mission to facilitate the transition of traditional textile units into technical textiles, supporting investment in high-growth areas such as medical, agro, and industrial fabrics.
- Development of seven Integrated Textile Parks (ITPs), which form the physical infrastructure backbone of the State's textile policy. Designed to enable industrial clustering and co-location of production processes, these parks are expected to generate over 29,000 jobs (Department of Textile, Tamil Nadu), while enhancing process efficiency, reducing logistics costs, and attracting FDI and private investment.

B5.2: Employment Linked Incentive Scheme

The Employment-Linked Incentive (ELI) scheme, initially posted in the 2024-25 Union Budget and approved by the cabinet in July 2025, is a direct fiscal intervention through a job-linked wage subsidy to promote formal hiring in the private sector.

Globally, several countries have deployed wage subsidies to increase employment among disadvantaged groups. Overall, the effectiveness of wage subsidies depends heavily on their design---untargeted subsidies without employer accountability or retention conditions often lead to temporary hiring with no long-term improvement. In contrast, strict conditions can reduce deadweight losses but increase administrative burden and lower take-up (ILO,2015).[8]

[8] *Slovenia's* wage subsidy, paired with training (Active Labour Market Programmes (ALMPs)), produced employment and earnings gains that lasted at least three years after completing the training programme. This has been especially effective for long-term unemployed and at-risk workers. *Switzerland's* temporary wage subsidies (TWS) for long-term immigrants and low-educated workers outperformed generic training programmes (significant positive medium-term impact on employment and earnings), delivering modest but sustained gains. Wage subsidies in Spain modestly increase permanent employment transitions, particularly for young and middle-aged workers, with young women benefiting the most. However, they do not substantially transform hiring behaviour. In Mexico, a temporary wage incentive significantly increased formal employment among vocational school graduates, especially through permanent contracts and higher retention. The intervention raised earnings by ~15 per cent and revealed that low-skilled youths may avoid formal jobs due to high reservation wages and distorted labour market incentives.

The first part of India's ELI scheme (Part A) is targeted towards first-time employees, registered with EPFO (Employee's Provident Fund Organisation) and earning salaries up to Rs 1 lakh per month, offering them a one-time one-month wage of up to Rs 15,000 in two instalments – one payable after 6 months of service and the second after 12 months and upon completion of a financial literacy programme by the employee.

The second part (Part B) is aimed at incentivising employers to hire and sustain additional employees, with salaries up to Rs 1 lakh per month, by offering the employers up to Rs 3,000 per month, for two years, for the hiring of each additional employee who stays on the job for at least six months. The benefits (Part B) follow a proportional wage bracket with the hiring of each additional employee per month providing Rs 1,000 to the employer if the employee earns up to Rs 10,000 per month, Rs 2,000 if the employee earns between Rs 10,000 and Rs 20,000 per month, and the maximum of Rs 3,000 if the employee earns between Rs 20,000 and Rs 1 lakh per month.

This dual-incentive structure is thus intended to reduce the effective cost of hiring and retaining workers for firms, while providing a temporary nudge toward formalisation.

However, concerns about creating sustainable employment remains. First, the scheme does not incorporate occupational skilling or job training to enhance productivity and create sustained employment. In the absence of investment in skilling new entrants or retaining them beyond a year, employers may rotate workers to show new hirings or compromise quality and reduce retention to maximise EPFO contributions. There is a risk of promoting short-term or low-quality jobs, sectoral imbalances favouring resource-rich industries and wage suppression or exploitation without adequate safeguards. Second, and relatedly, the scheme does not require periodical evaluations of long-term employment generation versus short-term costs. While the creation of the purported 3.5 crore beneficiaries may justify continued investment in the scheme, a comprehensive fiscal assessment should be provided at every milestone or every year with addendums on skilling and training the new entrants.

In conclusion, though the Employment-Linked Incentive (ELI) scheme has the potential to stimulate employment, the scheme's long-term impact will depend on careful targeting, robust implementation, and strong monitoring frameworks to avoid distortions or churning. Embedding complementary safeguards, such as retention clauses and co-financing mechanisms, can be established to ensure that employment generation is not temporary but sustains formal sector participation. For ELI to become more than a fiscal stimulus, it must be embedded within a broader state-level ecosystem of skilling, labour regulation reform, and decentralised execution, ensuring that employment creation is both durable and inclusive.

Annexures

Chapter 1 – Annexure

A1.1. Data Description

We have used several public datasets which are enumerated below by order of usage:

i. The World Bank Database

Cross-country data on real GDP per capita (2015 USD), population by age groups and proportion of wage and salaried workers as a percentage of total employment has been taken from the World Bank's Open Data portal (accessed in April 2025) for the period 1991- 2023 for a maximum sample size of 182 countries. The data on population by age has been used to construct the age dependency ratio (Figure 1.2a). Countries have been classified into different income categories (low income, low middle income, high middle income, and high income) following the World Bank 2017-18 Gross National Income (GNI) thresholds.

ii. The International Labour Organization Database on International Labour Statistics (ILOSTAT)

Cross-country data on employment, population, labour dependency, population by education levels and working-age population (ages 15+) with vocational education or training has been taken from the ILOSTAT database (accessed in April 2025) for the period 1991-2023 for a maximum sample size of 182 countries. The data on employment and population has been used to construct the workforce participation rate for ages 15+ (Figures 1.1a and 1.1b) and the youth workforce participation rate for ages 15-24 (Figures 1.2a and 1.2b). The data on population by education levels has been used to calculate the proportion of each country with at least higher secondary education levels for ages 15+ (Figures 1.1b and 1.6b). The data on working-age population by vocational education or training has been disaggregated by age groups to compute the share of youths (ages 15–24) with vocational training across countries (Figure 1.10a). 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 at the cross-country level.

iii. The Reserve Bank of India (RBI) Capital, Labour, Energy, Materials, and Services (KLEMS) database

Data on India's sectoral shares in total GVA and employment has been taken from the RBI KLEMS database (accessed in April 2025) for the period 1991- 2024 and used to construct the shares for agriculture, manufacturing, and services (Figures 1.3a and 1.3b).

iv. The Penn World Table (PWT) Database (version 10.01) by the Faculty of Economics and Business at the Groningen Growth and Development Centre, University of Groningen

Cross-country data on the number of persons employed (in millions) and capital stock (measured at constant 2017 USD prices in millions) has been taken from the PWT database (version 10.01, accessed in April 2025) for the period 1990 to 2018 for a maximum sample size of 181 countries and has been used to construct the labour-capital (L/K) ratio by dividing the number of persons employed by capital stock (Figure 1.4).

v. The Periodic Labour Force Survey (PLFS) by the National Statistical Office (NSO) of India

Data on India's self-employed workers and distribution of workers by training has been taken from the PLFS database (accessed in April 2025) for the period June 2017-18 to July 2023-24.

The data on self-employment has been used to calculate the proportion of self-employed workers in India as a percentage of total employment for rural males, rural females, urban males and urban females (Figure 1.7). The data on distribution of workers by training has been used to classify workers into formal training, informal training and no training categories (Figure 1.10b).

vi. The Economic Transformation Database (ETD) by the Faculty of Economics and Business at the Groningen Growth and Development Centre, University of Groningen

Cross-country data on the number of persons employed and GVA (measured at constant 2015 USD prices) has been taken from the ETD database (accessed in April 2025) for the period 1990-2018 for 51 non-OECD countries and has been used to construct the labour productivity (or output per worker) ratio by dividing GVA by the number of persons employed (Figure 1.8).

A1.2. Methodology

A1.2.1. Analysis of L/K ratio on per capita GDP

The cross-country labour-capital ratio (L/K ratio) analysis on per capita income has been conducted using the Penn World Table (PWT) database from the Groningen Growth and Development Centre, University of Groningen. We calculate the L/K ratio by dividing the number of persons employed (in millions) by the capital stock (measured in constant 2017 US$ in millions). The dataset covers 181 countries, and the time period has been uniformly taken for the period 1990-2018 to ensure conformability and comparability of results across different datasets. First, we present our analysis in the form of a scatter plot between L/K ratio and per capita GDP (Figure 1.4). The data on per capita GDP has been taken from the World Bank database.

Second, we empirically examine the relationship between L/K ratio and per capita GDP by running separate regression for a sample of eight countries (India, China, South Africa, Sri Lanka, Vietnam, Philippines, Cambodia, Bangladesh) over the period 1990-2018. This set of countries was chosen out of a set of BRICS countries (China and South Africa) and India's South-East Asian neighbours (Vietnam, Philippines, Cambodia, and Bangladesh) based on the availability of balanced data and comparable per capita income levels (in 2018). Due to potential endogeneity with country-level income, the analysis was kept at a univariate level. We thus assess how the L/K ratio responds to changes in real per capita income, while keeping country-specific characteristics separate.

We regress the log of L/K ratio (or labour-intensity) on the log of per capita GDP (both measured in constant 2015 USD), separately for each country, covering the period 1990 to 2018, according to the following equation:

$$\text{Log}(L/K)_t = \beta_0 + \beta_1 \text{Log}(\text{per capita GDP})_t + \epsilon_t \qquad \text{(Equation A1.1)}$$

where ϵ_t is a white noise error term.

The regression results are presented in Table A1.1. In order to test for significant differences in estimated coefficients between India and the other countries, we run a t-test to check for equality of estimated coefficients. The results are presented in the form of coefficient plots (covering the period 1990–2018) where countries with confidence intervals that do not overlap with India's are estimated to be significantly different from India's L/K ratio during that period (Figure 1.5). The results show a 1.21 per cent decrease in labour capital ratio with a 1 per cent increase in per capita income for India. The countries are arranged in descending order of per capita income (2018) and colour-coded for their respective World Bank income groups (with India separately highlighted at the top in pink).

Further, according to the coefficient plot, China and Cambodia have overlapping confidence bands with India and are hence comparable in terms of their labour-capital substitution rates over the period 1990-2018 (t-test). The remaining countries have significantly different coefficients from India. The level of significance for each country-level coefficient can be found from regression Table A1.1.

A1.2.2. Analysis of labour productivity on per capita GDP

The cross-country labour productivity analysis on per capita income has been conducted using the Economic Transformation Database (ETD) from the Groningen Growth and Development Centre, University of Groningen. We calculate labour productivity (or output per worker) by dividing the Gross Value Added (in constant 2015 USD) by the number of persons employed. The dataset covers 51 non-OECD countries over the period 1990-2018 and includes data on 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. We present our analysis for the aggregate GVA of all sectors, first, in the form of a scatter plot between labour productivity and per capita GDP (Figure 1.8). The data on per capita GDP is taken from the World Bank database.

Secondly, to empirically examine the relationship between labour productivity and real per capita income, separate regressions were conducted for our group of eight countries (India, China, South Africa, Sri Lanka, Vietnam, Philippines, Cambodia, and Bangladesh). Due to potential endogeneity with country-level income, the analysis was kept at a univariate level. We thus assess how labour productivity responds to changes in real per capita income, while keeping country-specific characteristics separate.

We regress the log of labour productivity (or GVA per worker) in year *t* on the log of per capita income (both measured in constant 2015 USD), separately for each country, covering the period 1990-2018, according to the following equation:

$$\text{Log(labour productivity)}_t = \beta_0 + \beta_1 \text{Log(per capita GDP)}_t + \epsilon_t \qquad \text{(Equation A1.2)}$$

where $\in_t$ is a white noise error term

The regression results are presented in Table A1.2. To test for significant differences in estimated coefficients between India and the other countries, we run a t-test to check for equality of estimated coefficients. The results are presented in the form of coefficient plots (covering the period 1990 to 2018) where countries with confidence intervals that do not overlap with India's are estimated to be significantly different from India's labour productivity during that period (Figure 1.9). The results show that a 1 per cent increase in per capita income leads to a 0.3 per cent increase in Value Added per worker for India. The countries have been arranged in descending order of per capita income (2018) and colour-coded for their respective World Bank income groups (with India separately highlighted at the top in pink).

Following the confidence band overlaps, Philippines, Cambodia, and Bangladesh have similar productivity changes to India's, with respect to per capita income (t-test). The other countries show significantly different estimates from India's. The level of significance for each country-level coefficient can be found from regression Table A1.2.

Table A1.1: Regression results of labour-capital ratio on per capita income

Log (Labour-Capital ratio) vs Log (Per Capita Income) (1990 - 2018)								
	India	**China**	**South Africa**	**Sri Lanka**	**Philippines**	**Vietnam**	**Cambodia**	**Bangladesh**
Log (Per Capita GDP)	-1.21***	-1.21***	-0.46***	-0.98***	-0.74***	-1.45***	-1.19***	-1.27***
	(-66.26)	(-52.82)	(-9.14)	(-38.67)	(-22.93)	(-76.20)	(-18.20)	(-98.26)
Constant	-1.95***	-0.41**	-7.85***	-3.14***	-4.90***	1.19***	-0.82*	-1.34***
	(-15.38)	(-2.21)	(-18.49)	(-15.83)	(-19.98)	(8.43)	(-1.78)	(-15.46)
Observations	29	29	29	29	29	29	29	29
R-square	0.99	0.99	0.73	0.98	0.97	1.00	0.81	1.00

Source: Penn World Table (1990-2018), Groningen Growth and Development Centre; World Bank Database; Authors' calculations.
***Note**:* t statistics in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Table A1.2: Regression results of labour productivity on per capita income

Log (Output per Worker) vs Log (Per Capita Income) across all Sectors combined (1990 - 2018)								
	India	**China**	**South Africa**	**Sri Lanka**	**Philippines**	**Vietnam**	**Cambodia**	**Bangladesh**
Log (Per Capita GDP)	0.30***	0.94***	-1.92***	-0.29***	0.25	0.034	0.39***	0.13***
	(3.70)	(15.86)	(-5.63)	(-3.77)	(1.63)	(0.64)	(5.02)	(3.64)
Constant	6.07***	0.97*	26.6***	11.5***	6.80***	7.86***	4.84***	7.12***
	(10.37)	(1.92)	(9.09)	(18.41)	(5.64)	(19.81)	(8.46)	(32.01)
Observations	29	29	29	29	29	29	29	29
R-square	0.37	0.94	0.48	0.27	0.059	0.024	0.12	0.41

Source: Economic Transformation Database (1990-2018), Groningen Growth and Development Centre; World Bank Database; Authors' calculations.
***Note**:* t statistics in parentheses.
* p<0.10, ** p<0.05, *** p<0.01.

Chapter 2 - Annexure

A2.1. Data Description

There are two main data sources used in this chapter:

A2.1a. The data for this study is sourced from the KLEMS India database.

Key variables include capital stock (K) at constant 2011-12 prices (in Rs crores), labour (L) measured as the number of persons employed (in '000s), and labour income shares in both Gross Output and Value Added.

The dataset covers 27 sectors including Agriculture, Hunting, Forestry, and Fishing, Mining and Quarrying, Manufacturing, Services, and Construction.

The manufacturing sector includes (2-digit codes):
Food Products, Beverages and Tobacco, Textiles, Textile Products, Leather and Footwear, Wood and Products of Wood, Pulp, Paper, Paper Products, Printing and Publishing, Coke, Refined Petroleum Products and Nuclear Fuel, Chemicals and Chemical Products, Rubber and Plastic Products, Other Non-Metallic Mineral Products, Basic Metals and Fabricated Metal Products, Machinery (nec), Electrical and Optical Equipment, Transport Equipment, and Manufacturing (nec) including Recycling.

The services sub-sectors include (2-digit codes):
Trade, Transport and Storage, Hotels and Restaurants, Post and telecommunication, Financial Services, Business Services, Public Administration, Education, Health and Social Work, and Other Services.

A2.1b. The data for this study is sourced from the Annual Survey of Industries (ASI) database.

The data for this study also draws from the Annual Survey of Industries (ASI), conducted by the Ministry of Statistics and Programme Implementation (MoSPI), Government of India.

Key variables extracted from ASI include total persons engaged (which covers workers directly employed, those employed through contractors, and supervisory/clerical/managerial staff), gross value added (GVA), and fixed capital. All monetary variables are converted to constant 2011–12 prices using the relevant WPI Index.

The ASI dataset is structured at the 2-digit NIC level, and this analysis includes the following manufacturing sectors: Food Products and Beverages, Tobacco Products, Textiles, Wearing Apparel; Dressing and Dyeing of Fur, Leather and Related Products, Wood and Products of Wood and Cork, except Furniture, Paper and Paper Products, Printing and Reproduction of Recorded Media, Coke and Refined Petroleum Products, Chemicals and Chemical Products, Pharmaceuticals, Medicinal Chemical and Botanical Products, Rubber and Plastics Products, Other Non-Metallic Mineral Products, Basic Metals, Fabricated Metal Products, except Machinery and Equipment, Machinery and Equipment n.e.c., Electrical Equipment, Computer, Electronic and Optical Products, Motor Vehicles, Trailers and Semi-trailers, Other Transport Equipment, Furniture and Other Manufacturing.

A2.2. Contribution of sectors and sub-sectors to GVA

Table A2.1: Share in total GVA – sub-sectors of the manufacturing sector

Sub-sector	1990	2001	2011	2023
Food Products, Beverages and Tobacco	0.020	0.020	0.019	0.014
Textiles, Textile Products, Leather and Footwear	0.017	0.018	0.020	0.019
Wood and Products of wood	0.008	0.004	0.003	0.002
Pulp, Paper, Paper products, Printing and Publishing	0.006	0.003	0.005	0.004
Coke, Refined Petroleum Products and Nuclear fuel	0.015	0.013	0.014	0.008
Chemicals and Chemical Products	0.017	0.025	0.024	0.027
Rubber and Plastic Products	0.003	0.007	0.007	0.007
Cement and other non-metallic minerals	0.010	0.011	0.011	0.010
Basic Metals and Fabricated Metal Products	0.024	0.026	0.031	0.029
Machinery, nec.	0.011	0.009	0.014	0.013
Electrical and Optical Equipment	0.004	0.004	0.010	0.009
Transport Equipment	0.008	0.010	0.015	0.018
Gems, Jewellery and Miscellaneous	0.003	0.004	0.004	0.008
Manufacturing	**0.146**	**0.155**	**0.177**	**0.169**

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

Table A2.2: Share in total GVA – sub-sectors of services sector

Sub-sector	1990	2001	2011	2023
Trade	0.072	0.085	0.097	0.114
Hotels and Restaurants	0.006	0.010	0.011	0.010
Transport and Storage	0.036	0.040	0.049	0.046
Post and Telecommunication	0.003	0.009	0.015	0.018
Financial Services	0.036	0.051	0.060	0.060
Business Service	0.014	0.036	0.055	0.107
Public Administration and Defense; Compulsory Social Security	0.062	0.064	0.061	0.056
Education	0.018	0.024	0.030	0.041
Health and Social Work	0.007	0.010	0.014	0.016
Other services	0.124	0.116	0.093	0.077
Services	**0.378**	**0.445**	**0.487**	**0.544**

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

Table A2.3: Share in total GVA – all sectors and sub-sectors

Sub-sector	1990	2001	2011	2023
Agriculture, Hunting, Forestry and Fishing	0.339	0.261	0.183	0.153
Mining and Quarrying	0.050	0.047	0.041	0.021
Food Products, Beverages and Tobacco	0.020	0.020	0.019	0.014
Textiles, Textile Products, Leather and Footwear	0.017	0.018	0.020	0.019
Wood and Products of wood	0.008	0.004	0.003	0.002
Pulp, Paper, Paper products, Printing and Publishing	0.006	0.003	0.005	0.004
Coke, Refined Petroleum Products and Nuclear fuel	0.015	0.013	0.014	0.008
Chemicals and Chemical Products	0.017	0.025	0.024	0.027
Rubber and Plastic Products	0.003	0.007	0.007	0.007
Cement & other non-metallic minerals	0.010	0.011	0.011	0.010
Basic Metals and Fabricated Metal Products	0.024	0.026	0.031	0.029
Machinery, nec.	0.011	0.009	0.014	0.013
Electrical and Optical Equipment	0.004	0.004	0.010	0.009
Transport Equipment	0.008	0.010	0.015	0.018
Gems, Jewellery & Miscellaneous	0.003	0.004	0.004	0.008
Electricity, Gas and Water Supply	0.020	0.024	0.022	0.024
Construction	0.067	0.069	0.089	0.088
Trade	0.072	0.085	0.097	0.114
Hotels and Restaurants	0.006	0.010	0.011	0.010
Transport and Storage	0.036	0.040	0.049	0.046
Post and Telecommunication	0.003	0.009	0.015	0.018
Financial Services	0.036	0.051	0.060	0.060
Business Service	0.014	0.036	0.055	0.107
Public Administration and Defense; Compulsory Social Security	0.062	0.064	0.061	0.056
Education	0.018	0.024	0.030	0.041
Health and Social Work	0.007	0.010	0.014	0.016
Other services	0.124	0.116	0.093	0.077
Total	1.000	1.000	1.000	1.000

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

A2.3. Classification of industries by labour intensity

Table A2.4: Labour to capital ratio manufacturing sub-sectors

Sector	Labour (LI) or capital (KI) intensive	1990	2001	2011	2023
Wood and Products of Wood	LI	0.232	0.142	0.063	0.035
Gems, Jewellery and Miscellaneous	LI	0.086	0.039	0.030	0.030
Textiles, Textile Products, Leather, and Footwear	LI	0.135	0.042	0.020	0.012
Electrical and Optical Equipment	LI	0.020	0.010	0.010	0.009
Food Products, Beverages, and Tobacco	LI	0.048	0.030	0.017	0.009
Cement and other non-metallic minerals	LI	0.079	0.023	0.014	0.008
Pulp, Paper, Paper Products, Printing, and Publishing	LI	0.005	0.005	0.005	0.006
Basic Metals and Fabricated Metal Products	KI	0.018	0.011	0.005	0.005
Machinery, nec.	KI	0.016	0.014	0.007	0.004
Rubber and Plastic Products	KI	0.023	0.009	0.007	0.004
Transport Equipment	KI	0.020	0.009	0.006	0.003
Chemicals and Chemical Products	KI	0.012	0.007	0.005	0.003
Coke, Refined Petroleum Products, and Nuclear Fuel	KI	0.005	0.001	0.001	0.001

Source: RBI KLEMS, 2024; Authors' calculations.
Note*:* i. LI refers to labour-intensive sub-sectors and KI refers to capital-intensive sub-sectors. ii. The median labour-to-capital ratio 0.006 for the year 2022-23 for the manufacturing sector. The sub-sectors with values equal to and above median of the manufacturing sector are classified as labour intensive.

Table A2.5: Labour to capital ratio services sub-sectors

Sector	Labour (LI) or capital (KI) intensive	1990	2001	2011	2023
Trade	LI	0.295	0.225	0.087	0.020
Hotels and Restaurants	LI	0.134	0.109	0.055	0.018
Education	LI	0.189	0.108	0.045	0.013
Health and Social Work	LI	0.139	0.069	0.025	0.011
Financial Services	LI	0.015	0.008	0.008	0.009
Transport and Storage	LI	0.016	0.018	0.014	0.009
Other Services	KI	0.006	0.005	0.003	0.004
Business Services	KI	0.016	0.008	0.004	0.003
Public Administration and Defense	KI	0.012	0.008	0.004	0.002
Post and Telecommunication	KI	0.010	0.008	0.005	0.001

Source: RBI KLEMS, 2024; Authors' calculations.

Note: i. L refers to labour-intensive sub-sectors and K refers to capital-intensive sub-sectors. ii. The median labour to capital ratio for the year 2022-23 is 0.009 for the services sector. The sub-sectors with values equal to and above median of the services sector are classified as labour-intensive.

Table A2.6: Labour to capital ratio all sectors and sub-sectors

Sub-sector	1990	2001	2011	2023
Agriculture, Hunting, Forestry and Fishing	0.164	0.132	0.080	0.052
Wood and Products of wood	0.232	0.142	0.063	0.035
Gems, Jewellery & Miscellaneous	0.086	0.039	0.030	0.030
Construction	0.180	0.103	0.046	0.023
Trade	0.295	0.225	0.087	0.020
Hotels and Restaurants	0.134	0.109	0.055	0.018
Education	0.189	0.108	0.045	0.013
Textiles, Textile Products, Leather and Footwear	0.135	0.042	0.020	0.012
Health and Social Work	0.139	0.069	0.025	0.011
Food Products, Beverages and Tobacco	0.048	0.030	0.017	0.009
Electrical and Optical Equipment	0.020	0.010	0.010	0.009
Transport and Storage	0.016	0.018	0.014	0.009
Financial Services	0.015	0.008	0.008	0.009
Cement and other non-metallic minerals	0.079	0.023	0.014	0.008
Pulp, Paper, Paper products, Printing and Publishing	0.005	0.005	0.005	0.006
Basic Metals and Fabricated Metal Products	0.018	0.011	0.005	0.005
Rubber and Plastic Products	0.023	0.009	0.007	0.004
Machinery, nec.	0.016	0.014	0.007	0.004
Other services	0.006	0.005	0.003	0.004
Chemicals and Chemical Products	0.012	0.007	0.005	0.003
Transport Equipment	0.020	0.009	0.006	0.003
Business Service	0.016	0.008	0.004	0.003
Mining and Quarrying	0.021	0.016	0.007	0.002
Public Administration and Defense; Compulsory Social Security	0.012	0.008	0.004	0.002
Coke, Refined Petroleum Products and Nuclear fuel	0.005	0.001	0.001	0.001
Electricity, Gas and Water Supply	0.002	0.001	0.001	0.001
Post and Telecommunication	0.010	0.008	0.005	0.001

Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. LI refers to labour-intensive sub-sectors and KI refers to capital-intensive sub-sectors. ii. The median labour-to-capital ratio 0.006 for the year 2022-23 for the manufacturing sector. The sub-sectors with values equal to and above median of the manufacturing sector are classified as labour-intensive iii. The median labour-to-capital ratio for the year 2022-23 is 0.009 for the services sector. The sub-sectors with values equal to and above median of the services sector are classified as labour-intensive.

We compare our classification and rankings with those of *Mundle and Sahu (2024)*, *R. Hasan (2013)* and *R. Kapoor (2014)*, and find that they are largely in alignment with ours.

Table A2.7: Consonance between classification across papers

	This study's classification Using 2015-16 L/K values for comparison	This study's classification Using 2022-23 L/K values for comparison
Mundle and Sahu (2024) The sub-sectors with the top 15 LK ratios have been classified as labour-intensive	0.783*** (0.000)	0.883*** (0.000)
Rana Hasan (2013)	0.667** (0.035)	0.667** (0.035)
Radhicka Kapoor (2014)	0.655** (0.040)	0.655** (0.040)

Note*:* i. The table presents the pairwise correlation values of labour intensity classifications across the papers ii. The figures in the parentheses are the p values. The significance levels are denoted by ***, **, * for 1 per cent, 5 per cent, and 10 per cent levels, respectively.

Table A2.8 provides the classification of the labour- and capital-intensive sub-sectors across the papers taken into consideration. It may be noted that the studies referenced do not cover all sectors considered in this analysis due to differences in aggregation levels and sectors included. We have conducted a broad assessment to check whether the classification of sub-sectors as labour- or capital-intensive aligns across studies. A sector/sub-sector classified as L is labour-intensive, and a sector/sub-sector classified as K is capital-intensive.

Table A2.8: Classification across papers

	Rank: My estimation (2015-16)	Rank: My estimation (2022-23)	Mundle and Sahu (2024)	Hasan (2013)	Kapoor (2014)
Agriculture, Hunting, Forestry and Fishing	LI	LI	LI		
Wood and Products of Wood	LI	LI		LI	LI
Construction	LI	LI	LI		
Hotels and Restaurants	LI	LI	LI		
Trade	LI	LI	LI		
Education	LI	LI	LI		
Gems, Jewellery and Miscellaneous	LI	LI	LI	LI	LI
Health and Social Work	LI	LI			
Textiles, Textile Products, Leather and Footwear	LI	LI	LI	LI	LI
Electrical and Optical Equipment	LI	LI		KI	
Transport and Storage	LI	LI			
Food Products, Beverages and Tobacco	LI	LI	LI	LI	LI
Cement and Other Non-metallic Minerals	LI	LI			
Financial Services	LI	LI	LI		
Machinery, nec.	LI	KI		KI	LI
Rubber and Plastic Products	KI	KI	KI	KI	KI
Pulp, Paper, Paper products, Printing and Publishing	KI	LI	LI	KI	LI
Basic Metals and Fabricated Metal Products	KI	KI	LI	KI	LI
Transport Equipment	KI	KI	KI		
Mining and Quarrying	KI	KI	KI		
Other Services	KI	KI			
Business Services	KI	KI			
Chemicals and Chemical Products	KI	KI	KI	KI	KI
Public Administration and Defence; Compulsory Social Security	KI	KI			
Post and Telecommunication	KI	KI			
Electricity, Gas and Water Supply	KI	KI	KI		
Coke, Refined Petroleum Products and Nuclear fuel	KI	KI	KI		KI

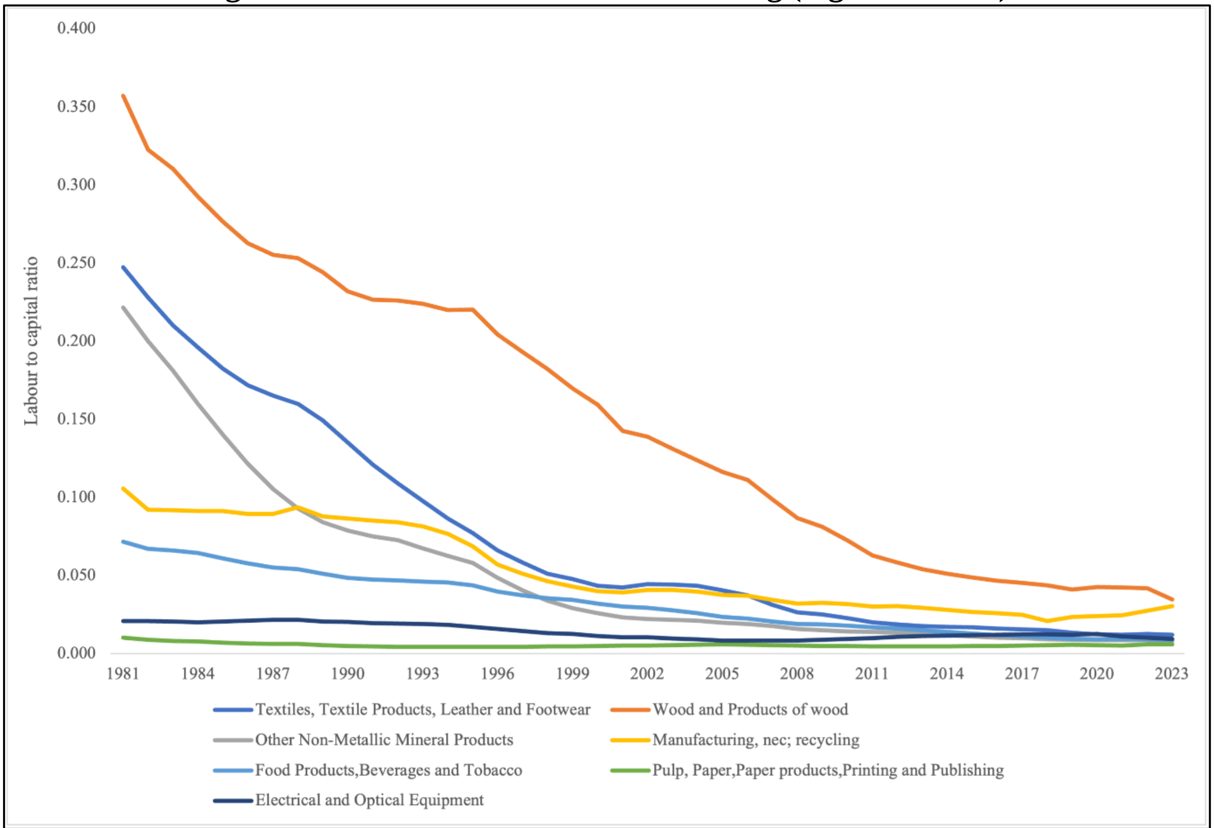
Source: RBI KLEMS, 2024; Authors' calculations.

Note: (i) The labour-to-capital (L/K) ratio represents the labour intensity of a sector. (ii) Data sources vary across studies. Kapoor (2014) uses the ASI database to estimate labour intensity. Hasan (2013) uses the ASI and NSS databases, while Mundle and Sahu (2024) use the PLFS and NSS datasets. (iii) 'Rank: My estimation (2022–23)' refers to this study's ranking of sub-sectors based on labour intensity in 2022–23. 'Rank: My estimation (2015–16)' refers to the ranking based on labour intensity in 2015–16.

A2.4. Additional Tables and Graphs

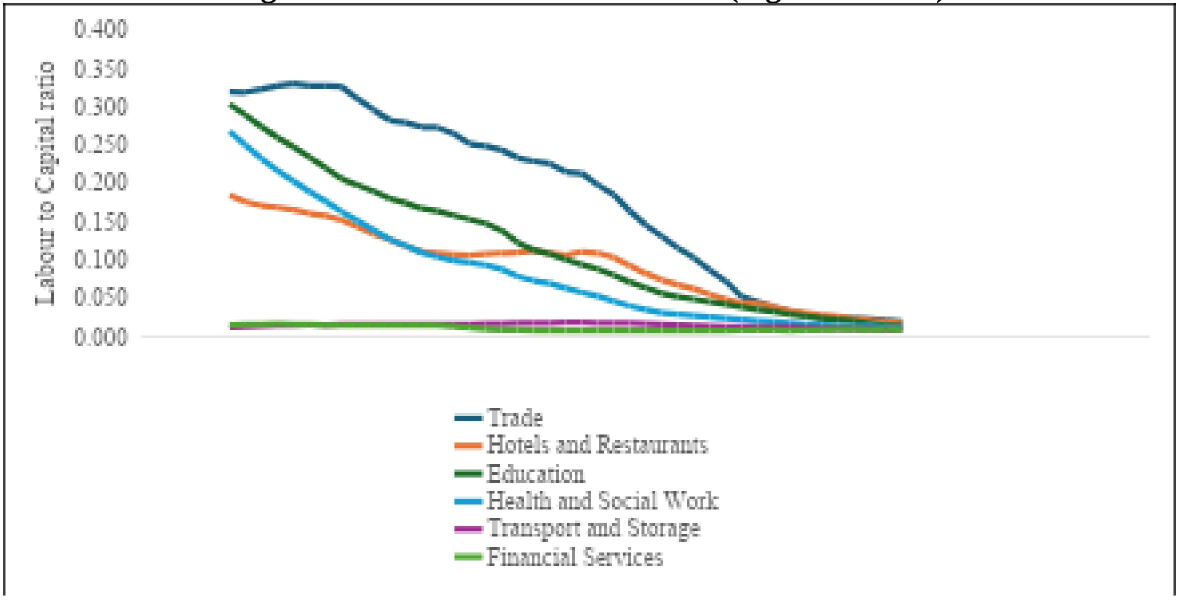
A2.4.1. Trends in L/K in the high and low labour intensity sub-sectors

Figure A2.1: Sub-sectors of manufacturing (high L/K ratio)



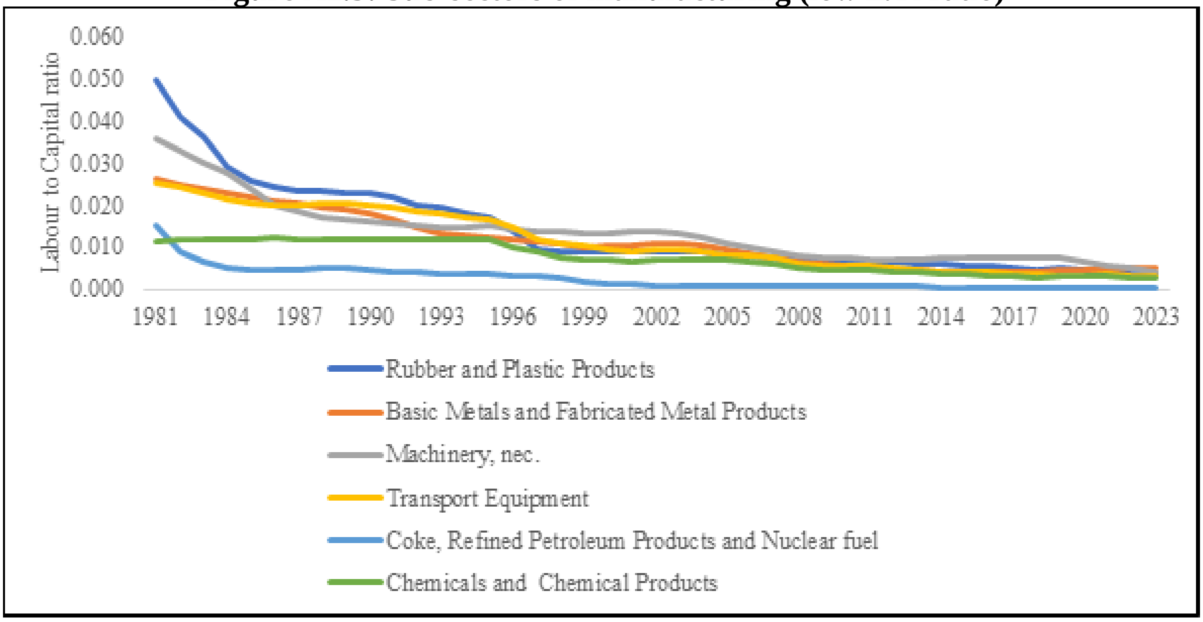
Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. L refers to Number of persons employed (in '000s) and K is the Capital stock in constant 2011-12 prices (Rs crores); ii. The Labour to Capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data; iv. The median Labour to Capital ratio is 0.006 for the year 2022-23 for the manufacturing sector. The sub-sectors with values equal to and above the median of the manufacturing sector are classified as labour-intensive.

Figure A2.2: Sub-sectors of services (high L/K ratio)



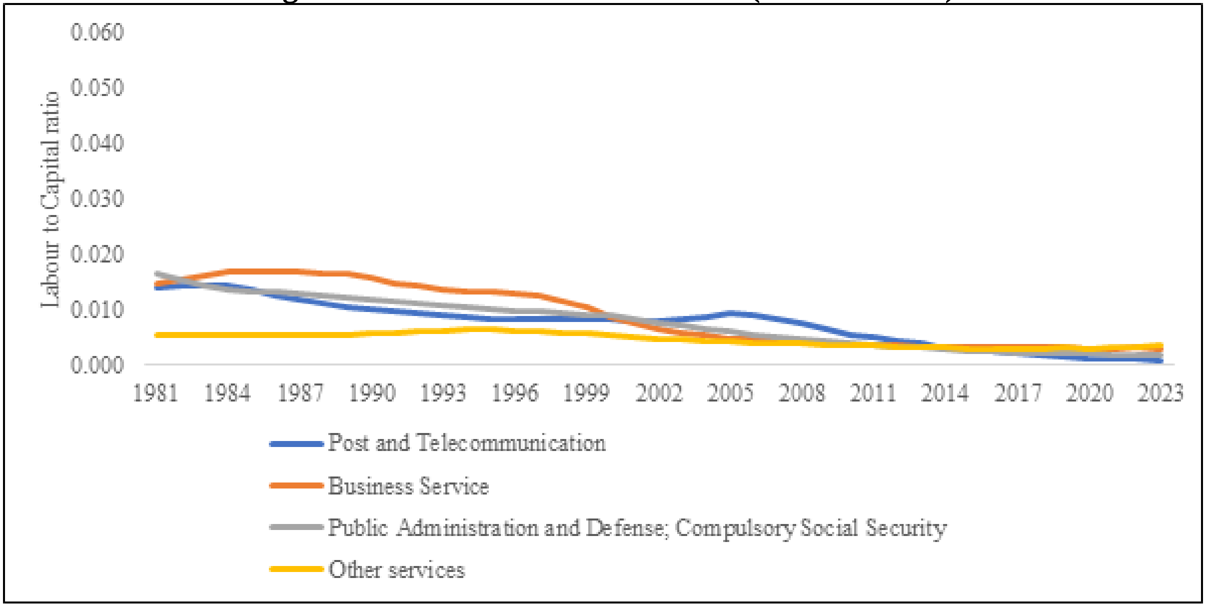
Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. L refers to Number of persons employed (in '000s) and K is the Capital stock in constant 2011-12 prices (Rs crores); ii. The Labour to Capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data iv. The median Labour to Capital ratio for the year 2022-23 is 0.009 for the services sector. The sub-sectors with values equal to and above the median of the services sector are classified as labour-intensive.

Figure A2.3: Sub-sectors of manufacturing (low L/K ratio)



Source: RBI KLEMS, 2024; Authors' calculations.
Note: i. L refers to number of persons employed (in '000s) and K is the capital stock in constant 2011-12 prices (Rs crores); ii. The Labour to Capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data; iv. The median Labour to Capital ratio is 0.006 for the year 2022-23 for the manufacturing sector. The sub-sectors with values below median of the manufacturing sector are classified as capital-intensive.

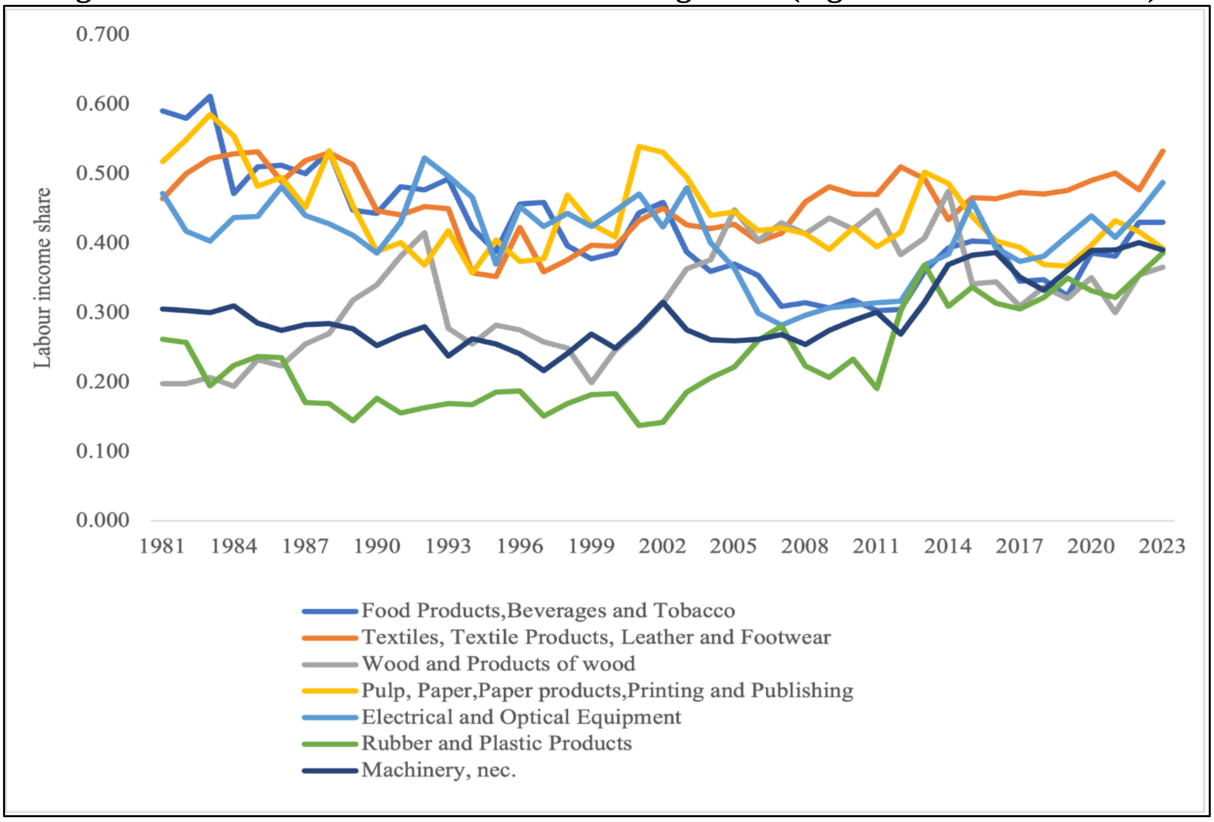
Figure A2.4: Sub-sectors of services (low L/K ratio)



Source: RBI KLEMS, 2024; Authors' calculations.

Note: i. L refers to number of persons employed (in '000s) and K is the capital stock in constant 2011-12 prices (Rs crores); ii. The Labour to Capital (L/K) ratio represents labour intensity of a sector; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data; iv. The median Labour to Capital ratio 0.009 is for the year 2022-23 for the services sector. The sub-sectors with values below the median of the services sector are classified as capital-intensive.

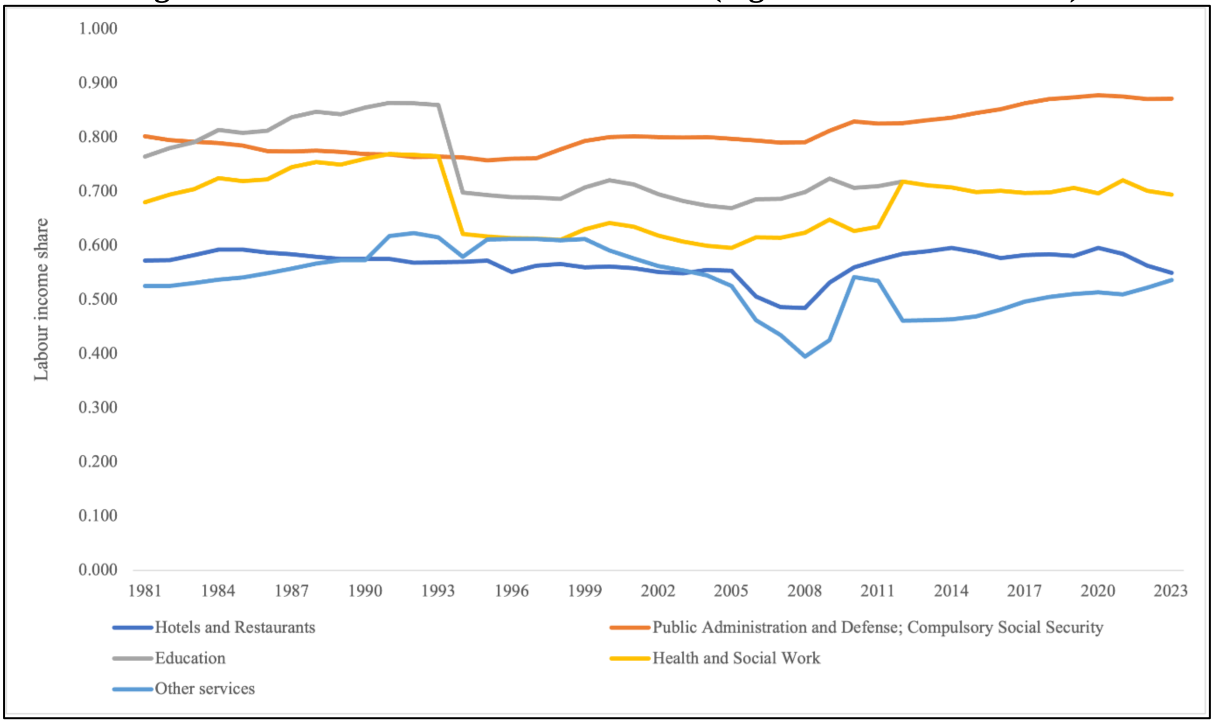
Figure A2.5: Sub-sectors of the manufacturing sector (high labour income share)



Source: RBI KLEMS, 2024.

Note: i. In the RBI KLEMS dataset, labour income is estimated using NAS, ASI, and unit-level survey data of unorganised manufacturing enterprises. Compensation of Employees (CE), Operating Surplus (OS), and Mixed Income (MI) are derived for 27 study industries; ii. Gross Value Added (GVA) is in 2011-12 constant prices; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data; iv. The median labour income as a share of Value Added for the year 2022-23 is 0.366 for the manufacturing sector. The sub-sectors with values equal to and above the median of the manufacturing sector are classified as high labour income share.

Figure A2.6: Sub-sectors of services sector (high labour income share)



Source: RBI KLEMS, 2024.
Note: i. In the RBI KLEMS dataset, labour income is estimated using NAS, ASI, and unit-level survey data of unorganised manufacturing enterprises. Compensation of Employees (CE), Operating Surplus (OS), and Mixed Income (MI) are derived for 27 study industries; ii. Gross Value Added (GVA) is in 2011-12 constant prices; iii. The dataset covers the period from 1981 through 2023, encompassing the entire span of available data; iv. The median labour income as a share of Value Added for the year 2022-23 is 0.522 for the manufacturing sector. The sub-sectors with values equal to and above the median of the manufacturing sector are classified as high labour income share.

A2.5. Share of labour income in GVA – Estimation

Income share of labour is computed in KLEMS as:

$$SL_t^i = \frac{CE_t^i + \left(\eta^i \times MI_t^i\right)}{GVA_t^i}$$

where,

SL_t^i is the labour income share in industry i in year t.
CE_t^i is compensation of employees in industry i in year t.
MI_t^i is mixed income of self-employed persons in industry i in year t.
GVA_t^i is the gross value added in industry i in year t.
η is labour income proportion in income. This is a fixed parameter and does not vary over time.

A2.6. Methodology to estimate employment elasticity

In the literature, employment elasticity is predominantly estimated using two methodologies: Compound Annual Growth Rate (CAGR) approach and log-log regression (Papola et al. (2012), Rangarajan et al. (2007); Misra and Suresh (2014)). We use the RBI KLEMS data to estimate elasticity coefficients.

Compound Annual Growth Rate (CAGR) Approach

The CAGR method is used to estimate *arc elasticity*, which represents the average responsiveness of employment to output growth over a specified period. Employment elasticity in this framework is calculated as the ratio of the Compound Annual Growth Rate of Employment to the Compound Annual Growth Rate of real Value Added:

Employment elasticity = $\frac{CAGR of employment}{CAGR of value added}$

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

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

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).

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.

$$logL_t = \alpha + \beta LogY_t + \epsilon_t$$

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).

A2.7. Employment Elasticity – Additional Tables

Table A2.9: Comparison of elasticity values across decades

	Manufacturing		Services		Agriculture	
	t statistic	*p value*	*t statistic*	*p value*	*t statistic*	*p value*
‘80s vs ‘90s	2.378	0.029	0.058	0.954	1.499	0.151
‘90s vs ‘00s	1.985	0.063	6.579	0.000	4.834	0.000
‘00s vs ‘10s	0.773	0.450	-2.543	0.020	-3.500	0.003
‘80s vs ‘10s	3.264	0.004	-0.161	0.874	-0.216	0.831

Source: RBI KLEMS, 2024; Authors’ calculations.

- *Manufacturing*: The difference between the 1980s and 2010s (1981-1990 and 2012-2023) is significant (p-value = 0.004), indicative of a significant change in the elasticity of the manufacturing sector over this period.
- *Services*: While the difference between the 1980s and the 2010s is not significant (p-value = 0.874), the elasticity values between the 1990s and 2000s are significantly different (p-value = 0.000). Elasticity in the services sector fell from 0.513 in the 1990s to 0.378 in the 2000s. However, the change from the 1980s to the 2010s is not significant, with elasticity at 0.523.
- *Agriculture*: A significant difference is observed between the 2000s and 2010s, indicating a decrease in elasticity for this sector between these periods.

Table A2.10: Employment elasticity estimations based on log-log regressions for labour-intensive sub-sectors

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

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

A2.8. Methodology to estimate employment multiplier

The Input-Output (I-O) framework models the inter-sectoral linkages within the economy and the values of inter-industry flows of goods and services. The Agriculture, Industry, Trade, Technology & Skills vertical of the National Council of Applied Economic Research (NCAER), constructed the 2018-19 IO using the Supply Use Table of the same year.

The National Statistical Office (NSO) releases Supply and Use Tables (SUT),[9] which comprises the Supply Table and the Use Table. The Supply Table presents details regarding

[9] Supply Use Table 2018-19: Note_Supply-Use_Tables_2017-18and2018-19.pdf

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 RBI KLEMS database.

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

Theoretical structure:

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

where,
X_i is the total output of ith sector.
X_{ij} is the total output of ith sector consumed in jth sector.
F_i is the total final demand for the ith sector consisting of private consumption.
We estimate the employment multiplier using the Input-output matrix based on the Supply-use Table 2018-19, MoSPI.

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

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

In Matrix notation:

$$(I - A)X = F$$

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

$(1 - A)^{-1}$ is the Leontief inverse

Labour output ratio:

$$E_i = \frac{L_i}{X_i}$$

Employment Multipliers:

$$L = E^\wedge \cdot (I - A)^{-1}$$

The total employment generated, or jobs created by each sector was estimated by multiplying the sector's gross output[10] for the year 2018-19 with the corresponding employment multiplier, derived from the input-output analysis. Considering the Supply Use Tables report information on current prices, we use current prices for the analysis pertaining to the I-O framework, to maintain consistency.

[10] We use Gross Output data from the RBI KLEMS database to estimate total employment and the number of direct jobs. This enables us incorporate information up to the year 2023.

Chapter 3 - Annexure

A3.1 Data Description

A3.1.1 PLFS data

This chapter primarily draws on unit-level person level data from the PLFS conducted by the NSSO, for the years 2017-18 to 2023-24. The analysis focuses on individuals aged 15–59 years, representing the core working-age population. All employment estimates are based on the Usual Status (Principal + Subsidiary) definition.

(i) Skills Categorisation

Skill categorisation is derived using the National Classification of Occupations (NCO) 2015 at the 1-digit level. Workers are grouped into three skill categories:

NCO Code	Occupational Description	Skill Level
1	Legislators, Senior Officials, and Managers	High-skilled
2	Professionals	High-skilled
3	Associate Professionals	High-skilled
4	Clerks	Medium-skilled
5	Service Workers and Shop & Market Sales Workers	Medium-skilled
6	Skilled Agricultural and Fishery Workers	Medium-skilled
7	Craft and Related Trades Workers	Low-skilled
8	Plant and Machine Operators and Assemblers	Low-skilled
9	Elementary Occupations	Low-skilled

(ii) Training Categorisation

Training categorisation is based on self-reported responses in PLFS regarding the type and source of skill training received. Workers are classified into three categories:

- Formally trained: Those who received training through recognised institutions or certification-based programmes.
- Informally trained: Those who acquired skills through hereditary learning, self-learning, on-the-job experience, or other non-institutional modes.
- Untrained: Those who reported no training of any kind.

(iii) Industry classification

Industry classification follows the 2-digit level of the National Industrial Classification (NIC) 2008. For the purposes of this chapter:

- Agriculture includes NIC codes 01 to 03.
- Manufacturing includes NIC codes 10 to 33.
- Services includes NIC codes 45 to 99.

Further, a subset of labour-intensive sectors is identified using RBI KLEMS data, based on a combination of high Labour-to-Capital (L/K) ratios and significant contributions to Gross

Value of Output (GVO). These sectors are grouped separately to assess employment and training trends in areas with high labour demand.

(iv) Sample weights and estimation

All estimates are weighted using the person-level multipliers provided in PLFS, ensuring that findings are representative at the national level.

A3.1.2 International Data

(i) **ILOSTAT**

Data from ILOSTAT (2023), the statistical database of the ILO are used to provide international context on vocational education and occupational skill levels. ILOSTAT reports country-level estimates for the working-age population (15+ years) with vocational education or training, disaggregated by age group, enabling the calculation of youth (15–24 years) vocational training shares. Additionally, it provides employment data by occupation classified by skill level, facilitating cross-country comparisons of workforce skill distribution.

(ii) **Education at a Glance Report, 2023**

Data on earnings and vocational education classifications for OECD countries are sourced from OECD (2023), Education at a Glance. Countries are classified by the dominant level of vocational education and training (VET) among adults aged 25–34 years, based on OECD's classification. The dominant VET level is defined as the level at which the majority of vocationally educated adults are concentrated—either upper secondary or short-cycle tertiary. Additionally, the report provides earnings data for adults aged 25–34 years by highest level of education attained. Specifically, it presents relative earnings for individuals whose highest qualification is at the upper secondary or post-secondary non-tertiary level, expressed as a ratio to the earnings of individuals with below upper secondary education (baseline = 100).

(iii) **Ministry of Manpower data, Singapore**

Employment and earnings data for Singapore are sourced from the Graduate Employment Survey, conducted by the Ministry of Manpower (MOM) in collaboration with local universities and polytechnics. The employment rate refers to the share of graduates employed approximately six months after completing their final examinations. For vocational tracks, the graduate cohort includes individuals who have completed National Service. The reported gross monthly starting salary includes basic salary, fixed allowances, overtime pay, and commissions, but excludes bonuses.

A3.2 Methodology and Results

A3.2.1. Impact of training on employment outcomes

The impact of training on employment outcomes in India (shown in Figures 3.12 and 3.13) are based on a logit regression model that is estimated at the individual worker level using PLFS data for 2024. The analysis is restricted to young workers aged 15 to 29 years, who represent the segment of the population transitioning into the workforce.

$$log\left[\frac{p\left(employed_{(it)}\right)}{1-p(employed_{it})}\right] = \beta_0 + \beta_1 training_{it} + \beta_2 gender_{it} + \beta_3 age_{it} + \beta_4 geduc_{it}$$

$$\beta_5 techedu_{it} + \beta_6 location_{it} + \gamma_s + \delta_t (equation\ A3.1)$$

where,

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

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

$gender_i$ is variable that takes value 1 for a male worker and 2 for female worker;

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

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

$techeduc_{it}$ 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;

γ_t are the state fixed effects;

ε_{it} is the error term.

A3.2.2. Simulation-based forecasting of employment outcomes (2025–2030)

The simulations in Section 3.5 are based on a logit regression estimated at the worker level using PLFS data for workers aged 15 to 59 years over the period 2018 to 2024. The specification is as follows:

$$log\left(\frac{p(employed_{it})}{1-p\left(employed_{(it)}\right)}\right) = \beta_0 + \beta_1 formaltraining_{it} + \beta_2 gender_{it} + \beta_3 age_{it} + \beta_4 geduc_{it}$$

$$+\beta_5 techedu_{it} + \beta_6 location_{it} + \gamma_s + \delta_t \qquad (equation\ A3.2)$$

where

For projecting employment for labour-intensive manufacturing,

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

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

$gender_i$ is the variable that takes value 1 for a male worker and 2 for female worker;

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

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

$techeduc_{it}$ 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.

The marginal impacts estimated from regression equation A3.2 capture the average change in the probability of employment associated with a one-unit increase in formal training, holding other factors constant. These marginal effects for employment in the manufacturing sector, services sector, and either sector are presented in Table A3.1.

Table A3.1: Regression results that indicate marginal impact of formal training on employment

Variables	Probability of being employed in manufacturing sector	Probability of being employed in services sector	Probability of being employed in either manufacturing or services
Formal training	0.09***	0.08***	0.12***
	(0.004)	(0.003)	(0.003)
Female worker	-0.29***	-0.45***	-0.47***
	(0.001)	(0.001)	(0.001)
Age	0.01***	0.01***	0.01***
	(0.00004)	(0.00004)	(0.00005)
Technical education below graduation level	0.06***	0.001	0.02***
	(0.004)	(0.004)	(0.004)
Technical education above graduation level	0.0002	0.07***	0.07***
	(0.004)	(0.004)	(0.004)
Above primary education	0.02***	0.06***	0.05***
	(0.002)	(0.002)	(0.002)
Above secondary education	-0.02***	0.16***	0.12***
	(0.002)	(0.002)	(0.002)
Urban area	0.03***	0.05***	0.05***
	(0.001)	(0.001)	(0.001)
Observations	1027493	1303547	1434391

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. Standard errors in parentheses; ii. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; iii. Other controls include state and time fixed effects.

The results show that an additional unit increase in formal training marginally raises the probability of employment by approximately 0.09 percentage points in the manufacturing sector, 0.08 percentage points in the services sector, and 0.12 percentage points in either the manufacturing or services sectors.

Using these marginal effects (denoted as Δ), the simulation estimates how changes in the share of formally trained workers impact employment in labour-intensive manufacturing, services, and the combined sector from 2025 to 2030, with 2024 as the base year. Specifically, the average change in employment probability per additional formally trained worker holding other factors constant, is used to project total employment changes under different hypothetical scenarios. The scenarios are identified based on changing either the share of formally trained workers in the workforce or the marginal effect obtained from logit model.

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

$$employment_{t+n} = employment_t + \left(\Delta_{t+n}.\left(N_{t+n}.\left(Sharef trained_{t+n} - Sharef trained\right)\right)\right)$$

$$(equation\ A3.3)$$

Where:

$employment_{t+n}$ is the projected employment in year t+n.

$employment_t$ is the actual employment in base year t.

Δ_{t+n} is the marginal effect under different scenarios in t+n period.

N_{t+n} refer s 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.

Table A3.2 presents the historical and projected year-on-year growth rates in the number of formally trained and untrained workers. It forms the basis for constructing three future training growth scenarios—baseline, moderate, and high—used in the simulation 1 and 2. The baseline growth rate is calculated as the average growth in the number of formally trained workers from 2018 to 2024, excluding 2020–21 due to the pandemic. The moderate and high scenarios assume growth that is 0.5 and 1 standard deviation above the baseline average, respectively. The number of untrained workers is assumed to grow at the baseline rate across all scenarios.

Table A3.2: Simulated year-on-year growth in the share of formally trained workers

Year	Number of formally trained workers	Number of untrained workers	YoY growth of formally trained workers	YoY growth of untrained workers	Baseline YoY growth of formally trained workers	Baseline YoY growth of untrained workers (average YoY growth, excluding 2020-21)	SD of YoY growth of formally trained workers	Moderate YoY growth of formally trained workers	High YoY growth of formally trained workers
2018	13591682	674515506	-	-	-	-	-	-	-
2019	16553832	676571979	21.8	0.3	18.3	1.8	13.3	24.9	31.5
2020	23039538	694635617	39.2	2.7	18.3	1.8	13.3	24.9	31.5
2021	23422867	691007915	1.7	-0.5	18.3	1.8	13.3	24.9	31.5
2022	25151775	715750866	7.4	3.6	18.3	1.8	13.3	24.9	31.5
2023	29236816	741520173	16.2	3.6	18.3	1.8	13.3	24.9	31.5
2024	31213646	734537326	6.8	-0.9	18.3	1.8	13.3	24.9	31.5

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The baseline uses the average year-on-year (YoY) growth for both formally trained workers and untrained workers from 2018 to 2024 (2021 is excluded from the average YoY growth calculation due to the impact of the pandemic); ii. The moderate and high growth scenarios assume that the YoY growth in formally trained workers is 0.5 and 1 standard deviation higher than this average, respectively, while the growth in untrained workers remains the same as in the baseline.

Tables A3.3 to A3.5 present the backend calculations for this simulation, estimating projected employment under three scenarios—baseline (Table A3.3), moderate growth (Table A3.4), and high growth (Table A3.5)—for the period 2025 to 2030.

Table A3.3: Calculations for simulation type 1 for baseline scenario

Year	Change in share of formally trained worker	Marginal impact of being formally trained			Total workers	Base employment in 2024 in labour-intensive manufacturing	Projected employment in 2024 in labour-intensive manufacturing	Base employment in 2024 in labour-intensive servicesring	Projected employment in 2024 in labour-intensive services	Base employment in 2024 in labour-intensive aggregate	Projected employment in 2024 in labour-intensive aggregate
		Labour-intensive manufacturing	Labour-intensive services	Labour-intensive aggregate							
2025	0.006	0.085	0.083	0.115	748073509	25038237	25458360	79556282	79963509	104594519	105161606
2026	0.013	0.085	0.083	0.115	761859138	25038237	25962988	79556282	80452647	104594519	105842759
2027	0.022	0.085	0.083	0.115	775898811	25038237	26567703	79556282	81038801	104594519	106659011
2028	0.031	0.085	0.083	0.115	790197210	25038237	27290940	79556282	81739838	104594519	107635245
2029	0.042	0.085	0.083	0.115	804759102	25038237	28154501	79556282	82576892	104594519	108800889
2030	0.054	0.085	0.083	0.115	819589343	25038237	29184176	79556282	83574962	104594519	110190758

Source: PLFS (2018 to 2024); Authors' calculations.

Note: Projected employment= Base year employment + (Change in share of formally trained workers (column3) × Total workers (column 6) × Marginal impact of training on employment (column 3))

Table A3.4: Calculations for simulation type 1 for moderate growth scenario

Year	Change in share of formally trained worker	Marginal impact of being formally trained			Total workers	Base employment in 2024 in labour-intensive manufacturing	Projected employment in 2024 in labour-intensive manufacturing	Base employment in 2024 in labour-intensive servicesring	Projected employment in 2024 in labour-intensive services	Base employment in 2024 in labour-intensive aggregate	Projected employment in 2024 in labour-intensive aggregate
		Labour-intensive manufacturing	Labour-intensive services	Labour-intensive aggregate							
2025	0.009	0.085	0.083	0.115	787061944	25038237	25628079	79556282	80131997	104594519	105390695
2026	0.019	0.085	0.083	0.115	810558930	25038237	26375710	79556282	80861723	104594519	106399856
2027	0.032	0.085	0.083	0.115	836728895	25038237	27320633	79556282	81784016	104594519	107675325
2028	0.047	0.085	0.083	0.115	866179034	25038237	28512195	79556282	82947040	104594519	109283709
2029	0.065	0.085	0.083	0.115	899666709	25038237	30012036	79556282	84410960	104594519	111308213
2030	0.086	0.085	0.083	0.115	938136823	25038237	31897155	79556282	86250932	104594519	113852770

***Source**:* PLFS (2018 to 2024); Authors' calculations.
***Note**:* Projected employment= Base year employment + (Change in share of formally trained workers (Column 3) × Total workers (Column 6) × Marginal impact of training on employment (Column 3)).

Table A3.5: Calculations for simulation type 1 for high growth scenario

Year	Change in share of formally trained worker	Marginal impact of being formally trained			Total workers	Base employment in 2024 in labour-intensive manufacturing	Projected employment in 2024 in labour-intensive manufacturing	Base employment in 2024 in labour-intensive services ring	Projected employment in 2024 in labour-intensive services	Base employment in 2024 in labour-intensive aggregate	Projected employment in 2024 in labour-intensive aggregate
		Labour-intensive manufacturing	Labour-intensive services	Labour-intensive aggregate							
2025	0.011	0.085	0.083	0.115	789133525	25038237	25834426	79556282	80292528	104594519	105619783
2026	0.025	0.085	0.083	0.115	815871570	25038237	26896446	79556282	81274591	104594519	106987362
2027	0.043	0.085	0.083	0.115	846949509	25038237	28308424	79556282	82580265	104594519	108805586
2028	0.065	0.085	0.083	0.115	883660909	25038237	30181029	79556282	84311887	104594519	111216967
2029	0.092	0.085	0.083	0.115	927706001	25038237	32659847	79556282	86604082	104594519	114408978
2030	0.124	0.085	0.083	0.115	981319942	25038237	35936395	79556282	89633947	104594519	118628236

Source*:* PLFS (2018 to 2024); Authors' calculations.
Note*:* Projected employment= Base year employment + (Change in share of formally trained workers (Column 3) × Total workers (Column 6) × Marginal impact of training on employment (Column 3)).

Tables A3.6 and A3.7 present the backend calculations for simulation 2 under moderate and high growth scenarios, respectively.

Table A3.6: Calculations for simulation type 2 for moderate growth scenario

Year	Change in share of formally trained worker	Marginal impact of being formally trained			Total workers	Base employment in 2024 in labour-intensive manufacturing	Projected employment in 2024 in labour-intensive manufacturing	Base employment in 2024 in labour-intensive servicesring	Projected employment in 2024 in labour-intensive services	Base employment in 2024 in labour-intensive aggregate	Projected employment in 2024 in labour-intensive aggregate
		Labour-intensive manufacturing	Labour-intensive services	Labour-intensive aggregate							
2025	0.009	0.087	0.085	0.117	787061944	25038237	25642301	79556282	80143883	104594519	105403457
2026	0.019	0.087	0.085	0.117	810558930	25038237	26407959	79556282	80888674	104594519	106428795
2027	0.032	0.087	0.085	0.117	836728895	25038237	27375665	79556282	81830008	104594519	107724709
2028	0.047	0.087	0.085	0.117	866179034	25038237	28595957	79556282	83017043	104594519	109358875
2029	0.065	0.087	0.085	0.117	899666709	25038237	30131962	79556282	84511187	104594519	111415831
2030	0.086	0.087	0.085	0.117	938136823	25038237	32062534	79556282	86389146	104594519	114001176

Source: PLFS (2018 to 2024); Authors' calculations.
Note: Projected employment= Base year employment + (Change in share of formally trained workers (Column 3) × Total workers (Column 6) × Marginal impact of training on employment (Column 3)).

Table A3.7: Calculations for simulation type 2 for high growth scenario

Year	Change in share of formally trained worker	Marginal impact of being formally trained			Total workers	Base employment in 2024 in labour-intensive manufacturing	Projected employment in 2024 in labour-intensive manufacturing	Base employment in 2024 in labour-intensive servicesring	Projected employment in 2024 in labour-intensive services	Base employment in 2024 in labour-intensive aggregate	Projected employment in 2024 in labour-intensive aggregate
		Labour-intensive manufacturing	Labour-intensive services	Labour-intensive aggregate							
2025	0.011	0.090	0.087	0.119	789133525	25038237	25834426	79556282	80328263	104594519	105652653
2026	0.025	0.090	0.087	0.119	815871570	25038237	26896446	79556282	81357993	104594519	107064075
2027	0.043	0.090	0.087	0.119	846949509	25038237	28308424	79556282	82727040	104594519	108940591
2028	0.065	0.090	0.087	0.119	883660909	25038237	30181029	79556282	84542709	104594519	111429279
2029	0.092	0.090	0.087	0.119	927706001	25038237	32659847	79556282	86946160	104594519	114723624
2030	0.124	0.090	0.087	0.119	981319942	25038237	35936395	79556282	90123086	104594519	119078150

***Source**:* PLFS (2018 to 2024); Authors' calculations

***Note**:* Projected employment= Base year employment + (Change in share of formally trained workers (Column 3) × Total workers (Column 6) × Marginal impact of training on employment (Column 3)).

A3.2.3. Estimating Training Requirements to Meet the Economic Survey Job Target

To assess the scale of skilling required to meet the Economic Survey target of generating 7.8 million jobs annually, Equation (A3.3) is rearranged to derive Equation (A3.4), which estimates the number of formally trained workers needed by year 2030. This calculation incorporates the marginal effect of training, the projected number of untrained workers, and the targeted employment increase.

$$x_{t+n} = \frac{1}{1 - shareftrained_t} . \left[\left(\frac{emptar_{t+n} - emp_t}{\Delta_{t+n}} \right) + (shareftrained_t \cdot y_{t+n}) \right]$$

$$(equation\ A3.4)$$

x_{t+n} is the share of formally trained workers required in year t+n.

y_{t+n} is the share of untrained workers in year t+n.

Δ_{t+n} is the marginal effect in year t+n.

$shareftrained_t$ is share of formally trained worker in base year t.

$emptar_{t+n} - emp_t$ is the difference between employment in base year and targeted employment as per the Economic Survey target in year t+n.

Table A3.8 presents the required share of formally trained workers under this target scenario. It shows that to meet the cumulative target of 46.8 million new jobs between 2025 and 2030, the share of formally trained workers in labour-intensive sectors must rise sharply from 4% in 2024 to 36% by 2030. This requirement is more than double the share projected even under the High Growth Scenario, which reaches only 16% by 2030.

Table A3.8: Projected share of formally trained workers if the Economic Survey job creation target is fully met within labour-intensive sectors

Scenario	Employment in aggregate labour-intensive sectors in 2024 ('000s)	Employment in aggregate labour-intensive sectors in 2030 ('000s)	Total Jobs created between 2030 and 2024	Increase in jobs created between 2030 and 2024 (%)	Share of formally trained workforce in 2024 (%)	Share of formally trained workforce in 2030 (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline scenario	104595	110191	5596	5.4	4	9
Scenario if economic survey target is met	104595	151395	46800	44.7	4	36

Source: PLFS (2018 to 2024); Authors' calculations.
Note: i. The classification of labour-intensive sectors is based on a high Labour-to-Capital (L/K) ratio and a significant contribution to GVO, calculated using RBI KLEMS data; ii. The required increase in the share of formally trained workers to meet Economic Survey employment target is estimated using equation 3.4 that links formal training to employment.

The target for job creation in labour-intensive sectors—assuming that all non-farm jobs are generated within these sectors—is 7.8 million per annum. Over six years (2025 to 2030), this results in a cumulative employment requirement of 46.8 million new jobs. As shown in Table A3.5, meeting this target would require the share of formally trained workers to increase from 4 per cent in 2024 to 36 per cent by 2030. This increase is significantly higher than even that projected under the high growth scenario, which assumes the share of formally trained workers rises only to 16 per cent.

Chapter 4 – Annexure

A4.1. Data Description

The Annual Survey of Unincorporated Sector Enterprises survey (ASUSE) focuses on the economic and operational characteristics of unincorporated, non-agricultural establishments in the manufacturing, trade, and services sectors. The unit of analysis for the ASUSE is an establishment. In 2023-24, a total of 498,024 establishments were surveyed, including 273,085 in rural areas and 224,939 in urban areas.

Rounds: ASUSE was initially launched on an experimental basis in 2019 for six months. However, data from this phase is not available. The first full-fledged annual survey commenced in April 2021 and was completed in March 2022 (ASUSE 2021-22). Since then, two additional rounds, ASUSE 2022-23 and ASUSE 2023-24, have been conducted, making unit-level data available from three survey rounds. The survey captures expenses, receipts, assets, loans, employment, etc. pertaining to the survey establishments besides other operational charterers.

Before ASUSE, NSSO has done various surveys of household enterprises such as:

- Unincorporated Non-Agricultural Enterprises (Excluding Construction) - JULY 2015 - JUNE 2016, 73 round

- Unincorporated Non-Agricultural Enterprises (Excluding Construction) - July-June 2010-11, NSS 67th Round

- Unorganised Manufacturing Enterprises Survey: NSS 62nd Round: July 2005 - June 2006

- Service Sector in India 2006-07, NSS 63rd round. Etc.

Sector-wise Coverage: ASUSE covers unincorporated non-agricultural establishments belonging to three sectors, viz., Manufacturing, Trade and Other Services (excluding construction).

Geographical Coverage: The survey covers the rural and urban areas of whole of India (except the villages in Andaman and Nicobar Islands which are difficult to access). The definitions of urban and rural areas as per census 2011

Ownership wise coverage: Unincorporated non-agricultural establishments pertaining to proprietorship, partnership (excluding Limited Liability Partnerships), Self-Help Groups (SHG), co-operatives, Private Non-Profit Institutions (NPIs) including Non-Profit Institutions Serving Households (NPISH) are covered.

Establishment types: Own Account Establishments (OAEs) and Hired Worker Establishments (HWEs).

Broad activity categories: manufacturing (25 activity categories), non-captive electricity generation, trade (5 activity categories) and other services (15 activity categories).

ASUSE Excludes

1. Incorporated establishments
2. Agriculture
3. Construction
4. Public Administration and Defence
5. Activities of households as employers
6. Extraterritorial organisations such as UN bodies

7. Monetary intermediaries such as commercial banks
8. Electricity units registered with CEA (central electricity authority of India)
9. Railways/Tramways/underground railways/air transport
10. Manufacturing units that are covered under ASI

Major Indicators

1. **Economic Indicators**
    1.1. Number of establishments
    1.2. Number of workers
    1.3. GVA per establishment
    1.4. GVA per worker
    1.5. Gross Value Output (GVO) per establishment
    1.6. Emolument per hired worker
    1.7. Market value of the establishment
    1.8. Outstanding loans of the establishment
2. **Operational Indicators**
    2.1. Type of Ownership
    2.2. Social Group of owner/Major partner
    2.3. Status of maintenance of Bank account
    2.4. Location of establishment
    2.5. Nature of Operation
    2.6. Registration status
    2.7. ICT Usage

Reference Period: *Last 30 days preceding the date of survey* or l*ast month* has been used as the reference period to collect most of the data. Various items of receipts and expenses as well as data on employment, emoluments, rent, interest, net surplus and value added for the establishments will be collected for the above reference period only. However, for seasonal establishments the reference period will refer to the last 30 days (preceding the date of survey), if they have worked continuously for last 30 days or more (including scheduled holidays) in the current season. For seasonal establishments which have worked for less than 30 days in the current season, last month will refer to an average month in the last working season.

Definitions

1. Enterprise: An institutional unit in its capacity as a producer of goods and services is known as an enterprise. An enterprise is an economic transactor with autonomy in respect of financial and investment decision-making, as well as authority and responsibility for allocating resources for the production of goods and services. It may be engaged in one or more economic activities at one or more locations. It may be noted that unincorporated enterprises owned by households, all of whose output is intended for final consumption or gross fixed capital formation by those households is outside the coverage of the definition of enterprises used in this round.

2. **Establishment**: An establishment is an enterprise, or part of an enterprise, that is situated in a single location and in which either only a single productive activity is carried out or in which the principal productive activity accounts for most of the Value Added. The enterprise and the establishment are the same for single-establishment firms.

The unit of enquiry of the ASUSE is an Establishment and not the Enterprise.

3. Non-agricultural establishment: All establishments covered under Sections ‘C’ to ‘S’ of NIC-2008 are "non-agricultural establishments".

4. Unincorporated non-agricultural establishments: Non-agricultural establishments which are not incorporated (i.e. registered under Companies Act, 1956; Companies Act, 2013) will only be covered. The coverage is restricted primarily to all household proprietary and partnership establishments.

In addition, society/trusts/associations/clubs/body of individuals etc., Co-operatives, Self Help groups (SHGs) and Private Non-Profit Institutions (NPIs) including Non-Profit Institutions Serving Households (NPISH) will be covered.

5. Own Account Establishment (OAE): An establishment which is run without any hired worker employed on a fairly regular basis (fairly regular basis means the major part of the period when operation(s) of an establishment are carried out during a reference period) is termed as an own account establishment.

6. Hired Worker Establishment (HWE): An establishment which is employing at least one hired worker on a fairly regular basis is termed as hired worker establishment. Paid or unpaid apprentices, paid household member/servant/resident worker in an establishment are considered as hired workers.

7. Perennial establishment: Establishments that are run more or less regularly throughout the year are called perennial establishments.

8. Seasonal establishment: Seasonal establishments are those which are usually run in a particular season or fixed months of a year.

9. **Casual establishment:** Establishments that are run occasionally, for a total of at least 30 days in the last 365 days, are called ‘casual establishments.

A4.2 Tables

Table A4.1: Trends in total enterprises and employment by type and sector

Year	OAE	HWE
Total Enterprise		
2021-22	5,11,70,499	82,83,542
2022-23	11,05,21,370	1,90,22,001
2023-24	6,70,49,711	98,45,734
Total Employment		
2021-22	632,28,900	346,57,100
2022-23	679,52,500	416,73,000
2023-24	764,68,700	441,22,500
Total Employment (Manufacturing)		
2021-22	190,07,200	89,18,900
2022-23	191,63,600	114,61,900
2023-24	218,99,800	117,97,900
Total Employment (Services)		
2021-22	442,21,700	257,38,200
2022-23	487,88,900	302,11,100
2023-24	545,68,900	323,24,600

Source: ASUSE 2021-22 to 2023-24.
Note: Services sector includes trade.

Table A4.2: Share and sources of loans accessed by enterprises (2021–22 to 2023–24)

Loan Source	2021-22	2022-23	2023-24
Central and state level term lending institutions	31.1	46.0	30.1
Government (central, state, local bodies) scheme	298.4	407.9	520.6
Commercial banks	1887.6	2659.6	3031.6
Co-operative banks and societies	507.2	511.6	468.1
Micro-finance institutions/SHGs	878.4	746.6	728.9
Other institutional agencies	164.5	118.3	132.5
Money lenders	598.1	731.1	533.0
Business partner(s)	6.7	34.2	35.4
Suppliers/contractors	713.7	1246.9	1087.5
Friends and relatives	1424.5	1661.3	1522.4
Others	101.4	124.9	82.4
Total Enterprises with loans	6155.4	7860.6	7835.3
Total Enterprises without loans	53547.3	57187.8	69300.3
Total Enterprises	59702.7	65048.4	77135.6
Share of enterprises with loans	**10.3**	**12.1**	**10.2**

Source: ASUSE 2021-22 to 2023-24.

A4.3. Methodology

a) Correlation between hired workers and GVA

To visualise the relationship between employment and economic output, Figure 4.8 presents a scatter plot of Total Workers against Real Gross Value Added (GVA) for the HWEs at the firm level. To reduce the influence of extreme values, we restrict the sample to firms with GVA less than Rs 20 crores and total workers fewer than 500. This restriction retains 99.9 per cent of the total observations (47,017 out of 47,046). Each point in the scatter plot represents an individual firm. A linear fit line is overlaid on the scatter plot to capture an average relationship between workers and GVA.

Table A4.3: Correlation tables

Variable 1	Variable 2	Correlation	P-value
workers_total	GVA_real	0.3460	0.0000

Source: ASUSE 2021-22 to 2023-24; Authors' calculations.

Regression table

Variable	Coefficient	Std. Err.	t	P>|t|	95% Conf. Interval
GVA_real	6.26e-07	7.83e-09	79.97	0.000	[6.14e-07, 6.41e-07]
_cons	5.7787	0.0504	114.64	0.000	[5.6799, 5.8775]

Model Summary

Observations	**47,017**
R-squared	0.1197
Adj. R-squared	0.1197
Root MSE	10.691
F-statistic	6394.76
Prob > F	0.0000

b) GVA quintile regression

We analyse the determinants of hiring workers in the distribution of GVA. The analysis is based on pooled cross-sectional data from the ASUSE surveys for the years 2021–22 to 2023–24. ASUSE collects GVA data for only for enterprise which are involve in market production and in the pooled data there were 9,103 enterprises which were not involved in market production, so these enterprises are dropped. Further, 10 -12 per cent enterprises (2021-22 – 10.3 per cent, 2022-23 – 12.1 per cent and 2023-24 – 10.2 per cent) have reported information about outstanding loans. Since there are no alternative sources to verify the loan status of the sample enterprises, and not possible to determine whether these enterprises lacked access to credit, did not require it, or simply did not report it, they are excluded from the analysis.

Therefore, for the purpose of regression analysis, the sample is restricted to enterprises that reported at least one worker and have reported some information about the loan, which gave us 156,630 enterprises (weighted number 2.2 crore enterprises).

The dependent variable is the real Gross Value Added of enterprises, and separate regressions were estimated at the 10th, 25th, 50th, and 75th percentiles of the GVA distribution to capture the heterogeneous effects of various enterprise characteristics across the GVA distribution. This analysis uses real GVA as a proxy for enterprise productivity and growth potential. By identifying the key drivers of higher GVA (such as access to credit, technology adoption, proprietor education, and industry characteristics), it provides insights into the conditions that enable Own Account Enterprises (OAEs) to enhance their productivity and earnings. Such improvements are critical prerequisites for the transition from OAEs to Hired Worker Enterprises (HWEs), thus promoting both employment generation and economic upgrading.

The model includes key explanatory variables such as access to institutional credit, technology usage, training of the proprietor, and controls for year and state fixed effects. The specifications are as follows:

$$
\begin{aligned}
log(Worker_i) \\
&= \beta_0 + \beta_1 AccessCredit_i + \beta_2 TechUse_i + \beta_3 Training_i + \beta_4 Education_i \\
&+ \beta_5 Sector_i + \delta_t Year_t + \gamma_s State_s + \varepsilon_i
\end{aligned}
$$

... (equation A4.1)

Where:

$Worker_i$ = Total number of workers in $enterprise_i$.

$AccessCredit_i$ = 1 if the outstanding loan of enterprise is from formal sources, 0 if the outstanding loan of enterprise is from informal sources.

$TechUse_i$ = 1 if the enterprise uses computer/internet, 0 otherwise.

$Training_i$ = 1 if proprietor / major partner has completed any technical/ professional/ vocational courses, 0 otherwise.

$Education_i$ = Education level of the proprietor.

$Sector_i$ = 1 Manufacturing, 2 if Services.

$\delta_t Year_t$= Year fixed effects (to control for time trends with 2022 as benchmark year).

$\gamma_s State_s$ = State fixed effects (to control for regional heterogeneity).

ϵ_i = Error term.

Table A4.4: Quantile regression analysis

	10^{th} Quantile	25^{th} Quantile	50^{th} Quantile	75^{th} Quantile	90^{th} Quantile
Access to institutional credit (Ref: No)					
Yes	41,216***	74,992***	156,653***	342,565***	644,188***
	(2,076)	(3,025)	(5,781)	(15,271)	(59,589)
Use Tech (Ref: No)					
Yes	38,188***	63,328***	130,946***	303,843***	693,485***
	(2,176)	(3,170)	(6,059)	(16,005)	(62,451)
Technical/Vocational Training of Proprietor (Ref: No)					
Yes	23,633***	42,130***	73,307***	108,970***	114,821
	(2,673)	(3,894)	(7,443)	(19,661)	(76,719)
Proprietor Edu Level (Ref: Illiterate)					
Below Primary	4,310	619.3	-17,208	-37,370	-19,807
	(9,352)	(13,627)	(26,044)	(68,799)	(268,454)
Below Secondary	8,712	9,938	-1,986	-13,387	-16,309
	(8,295)	(12,088)	(23,100)	(61,024)	(238,117)
Secondary	21,973***	26,439**	24,882	31,370	49,794
	(8,237)	(12,003)	(22,939)	(60,597)	(236,451)
Higher Secondary	32,437***	49,390***	72,819***	108,386*	225,982
	(8,309)	(12,108)	(23,139)	(61,127)	(238,519)
Grd & above	58,446***	104,859***	224,430***	626,233***	1.630e+06***
	(8,315)	(12,116)	(23,155)	(61,167)	(238,676)
Sector (Ref. Manufacturing)					
Services	-39,912***	-70,042***	-141,394***	-255,816***	-429,686***
	(2,050)	(2,988)	(5,710)	(15,083)	(58,856)
Constant	109,721***	182,847***	347,861***	719,183***	3.018e+06***
	(14,414)	(21,004)	(40,141)	(106,039)	(413,766)
Pseudo R2	0.0134	0.0182	0.032	0.0526	0.0648
Observations	47,046	47,046	47,046	47,046	47,046

Source: ASUSE 2021-22 to 2023-24; Authors' calculations.

c) Predicted values calculation

The predicted GVA is calculated as:

Predicted GVA = Intercept + Coefficient

This formulation allows us to isolate the contribution of access to credit or technology to GVA, holding other influencing factors constant. Small, medium, and big businesses in the graphs correspond to the 10^{th}, 50^{th}, and 90^{th} percentiles of the GVA distribution, respectively. This method provides a meaningful comparison between actual and potential enterprise performance and highlights the transformative impact of credit and technology in enhancing enterprise productivity.

d) OLS regression

While the previous estimations demonstrate that factors such as access to credit, technology use, and training contribute to higher GVA, the core objective of this analysis is to assess whether higher enterprise productivity (as measured by GVA) translates into increased employment. In other words, does a rise in GVA lead to the creation of more jobs within enterprises?

To assess whether higher enterprise productivity translates into greater employment, we estimate an Ordinary Least Squares (OLS) regression model where the dependent variable is the log of total hired workers in the enterprise. The key explanatory variable is the log of Gross Value Added (GVA), used as a proxy for enterprise productivity. The model controls for various enterprise-level characteristics, including:

- Access to institutional credit
- Use of technology
- Proprietor's vocational/technical training
- Proprietor's education level
- Sector of activity

Table A4.5: OLS regression results

VARIABLES	HWE sample
GVA	
Log GVA	0.405***
	(0.00334)
Access to institutional credit (Ref: No)	
Yes	0.0266***
	(0.00436)
Use Tech (Ref: No)	
Yes	0.0254***
	(0.00442)
Technical/Vocational Training of Proprietor (Ref: No)	
Yes	-0.00406
	(0.00565)
Proprietor Edu Level (Ref: Illiterate)	
Below Primary	-0.0253
	(0.0181)
Below Secondary	-0.0739***
	(0.0162)
Secondary	-0.0891***
	(0.0162)
Higher Secondary	-0.0803***
	(0.0164)
Grd & above	-0.0166
	(0.0165)
Sector (Ref. Manufacturing)	
Services	-0.177***
	(0.00439)
Constant	-3.564***
	(0.0546)
Pseudo R2	0.608
Observations	46,938

Source: ASUSE 2021-22 to 2023-24; Authors' calculations.
Note*:* Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

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