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66th ANNUAL CONFERENCE

19-21 January 2026 | Symbiosis School of Economics, Symbiosis International (Deemed) University, Pune, India

Education, Employment and the Indian Labour Market: An Assessment of Sustainability Transition

KEYNOTE PAPER

BINO PAUL
Professor, Tata Institute of Social Sciences, Mumbai

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By
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Education, Employment and the Indian Labour Market: An assessment of sustainability transition

Bino Paul[1]

Abstract

For a socio-economic system, coherence between education and employment is crucial for its sustainability. India presents a unique case of abundance in people and skills, while its economy is in expansion. Although access to schools and higher education has increased substantially over the years, India's generation of quality jobs for fresh entrants to the labour market remains a question of concern. While the literature is replete with empirical studies on outcomes such as employment, wage, unemployment, and labour force participation, assessing whether education and employment move in tandem and generate quality jobs sustainably opens new policy dimensions for decent employment in the context of disruptive technologies and sustainability transitions. An educational system that provides relevant and realistic knowledge and experience connects aspirants with desirable labour-market outcomes, such as decent jobs, earning a living wage, improving the family's living standard, enhancing wellness, participation in creative activities, and redemption from the clutches of inequality. A transition to a sustainable impact pathway requires that outcomes be inclusive, not having over-reliance on regions or identities. Using the microdata and other evidence, we explore the co-movement of education and employment over the last decade in India, particularly to build an understanding of the dynamics of decent jobs for youth. Moreover, the paper engages with essential questions of how the labour market responds to new technologies and the growing realm of the circular

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economy. From a policy perspective, the patterns analysed in the paper provide helpful cues for examining the sustainable trajectories of public education finance. Another curious aspect is the Government policy on employment-linked incentives. While the policy aims to create many jobs, it assumes a strong link between education and industry. As discussed in the extant literature, micro, small and medium industrial units remain significant sources of employment. Many of these firms are part of the value chains involving large firms. Their upgrading is not necessarily the substitution of labour. Instead, it is a transition to more skilled jobs. We examine whether evidence points to this pathway. The paper will discuss probable impact pathways for the policy. By integrating empirical evidence with policy analysis, we advance the discourse on sustainable employment transitions in India.

Key Words: **Education, Quality Employment, Labour Market Outcomes.**

1. Introduction

The dimension of sustainability is not confined to environmental or economic contexts. It is incomplete without social dimensions. Aligning cleaner technologies with business value creation involves upgrading not just technological capability; it is indispensable to harness human potential for the change. In this milieu, education is a catalyst for transformations. This connection is vital in higher education because it is directly aligned with productive capacities. The schooling, to an extent, culminates in the progress of persons to higher education, then to the workplace, or any stream of livelihood or living.

The organic interdependence between higher education, the economy, and the labour market shapes the sustainability transitions. For example, the journey to a green economy requires a labour force with the knowledge and skills to implement processes and collaborate with diverse stakeholders. In this milieu, we explore the economy's journey over the last four decades and examine the role of labour in the system. We assess the current state of the Indian higher education system, particularly in terms of quality. Here, we interlink labour quality and outcomes. Aligning the economy and higher education raises questions about the nature of labour-market outcomes for recent graduates and postgraduates.

How do they fare in the job market? Do they land jobs with good pay and entitlements? Is higher education transformative? Some of these questions shape our exploration. The question is: do we have scientific evidence that higher education transforms youth's lives? Unemployment is a risk in higher education despite its benefits, and it is underutilising the potential. How, then, do job aspirants cope? Also, we examine whether higher education translates into participation in the green economy.

The paper is descriptive and analytical. We use multiple data sets to engage with these questions. To understand economic dynamics, we rely on the Reserve Bank of India's (RBI) KLEMS database, spanning four decades (1980-81 – 2022-23). Regarding Indian higher education, we use secondary data from the All-India Survey on Higher Education (AISHE) and the National Institutional Ranking Framework (NIRF). We analyse the Periodic Labour Force Survey (PLFS) 2023-24 microdata to understand the labour market dimensions. We used a mix of descriptive and inferential analysis. The data were described using cross-sectional plots. For the inferential part, we applied panel regression models, network models, and a Bayesian A/B test.

The paper consists of eight sections. Section 2 discusses the dynamics of labour and select macro aggregates. Section 3 presents the recent quality and quantity dimensions of Indian higher education. Section 4 provides an overview of the labour market for young graduates and postgraduates aged 22-27. Section 5 discusses the impact of higher education on labour-market transitions. Section 6 outlines the duration of unemployment and the job search. Section 7 discusses the participation of higher-education recipients in the green economy. Section 8 concludes the paper.

2. Positioning Employment in the Economy

We examine the co-movement between, value added, labour and capital. Figure 1 delineates the relationships among Employment (LnL), Capital (LnK), Real Value Added (LnVA), Ln(VA/L), and Capital per Labour (Ln(K/L)) in India over the last four decades. While we examine the trend for the economy as an aggregate, we also look into trends for agriculture (LnL_a, LnK_a, LnVA_a, Ln (V/L) _a, Ln (K/L) _a), manufacturing (LnL_m, LnK_m, LnVA_m, Ln (V/L) _m, Ln (K/L) _m) and service (LnL_s, LnK_s, LnVA_s, Ln (V/L) _s, Ln (K/L) _s). For the whole economy, the employment has been responsive to change in the value added (figure A). It is a mix of inelastic and elastic

changes. However, the capital-valued added relationship is steadier than it is with the employment (figure B).

The ratio of valued added to labour (Ln (VA/L)), a proxy for labour productivity, shows a direct relation, despite variation in the slope (figure C). Concerning agriculture, the relationship between LnL_a and LnVA_a is nonlinear. First the relationship is direct, reaching a plateau, and then plummeting consistently. In next phase (figure D), there is a slight uptick. However, LnK_a shows a direct relation with LnVA_a throughout the period of analysis (figure E). The direction relation also applies to labour productivity Ln (V/L)_a and capital labour ratio (Ln (K/L)_a) (figure F). In the case of manufacturing, figure G depicts a mixed pattern of consistent increase and visible saturation in the relationship between LnL_m and LnVA_m. In the recent times, there is a discernible stagnation in employment creation in Indian manufacturing. However, capital shows a consistently direct relation with value added (figure H). Further, labour productivity also shows a steady direct relationship with capital labour ratio (figure I). Concerning service, all three figures J, K, and L), show direct relations.

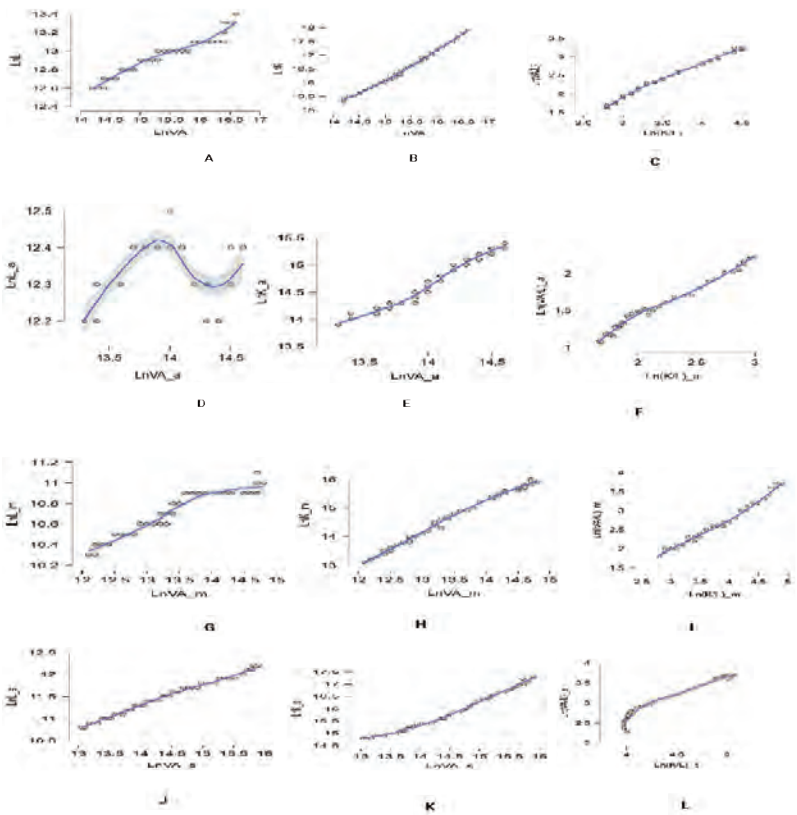
The story emerging from these figures is that employment expanded, with value added, during 1981-82 – 2022-23. However, the agricultural pattern shows an inverted U-shaped pattern, with a recent slight uptick. During the initial decades, employment grew in line with value added, then plateaued. Post that phase, the relationship turned negative. However, the capital maintained a steady direct relation with value added. Looking at the graph, there are three phases: a relatively slower expansion of capital with respect to changes in value added, a more rapid change, and a slow-paced covariation. Labour productivity is becoming more responsive to changes in the capital-labour ratio. The change is evident due to greater economic diversification and growing migration from rural to urban areas. Should the stereotypical shrinkage of farming employment be viewed as a sign of a growing economy?

Or diversifying the farming economy itself is an opportunity to generate a value-adding, productive employment system. In manufacturing, job creation has been near stagnation in recent decades. On the other hand, capital is in constant expansion relative to growing value added. Moreover, labour productivity seems to be more positively inclined to change in the capital-labour ratio. If we compare patterns for agriculture and manufacturing, shrinkage in agricultural employment does not convert into expansion in manufacturing employment.

However, service remains absorptive of labour throughout the last four decades, maintaining a steady increase with respect to growth in value added. Also, capital maintained steady growth along with the expansion of value added. The same pattern applies to the relation between labour productivity and capital-labour ratio. Although the extant literature routinely observes that service increasingly absorbs job seekers in India and that manufacturing jobs stagnate, what remains curious is what this implies for the growing flow of educated youth. The ensuing discussion will throw light on the plural contours of this problem.

Figure 1

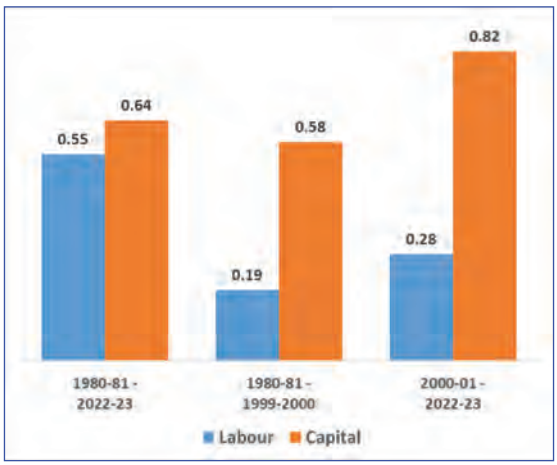
Real Value Added, Employment, and Real Capital in India



Source: based on the KLEMS database, Reserve Bank of India (1980-81 to 2022-23)

Real Values are based on 2011 prices.

Figure 2
Estimating the long-run relationship between Real Value Added, Labour, and Real Capital (Coefficients)



Source: Computation is based on RBI KELMS Data

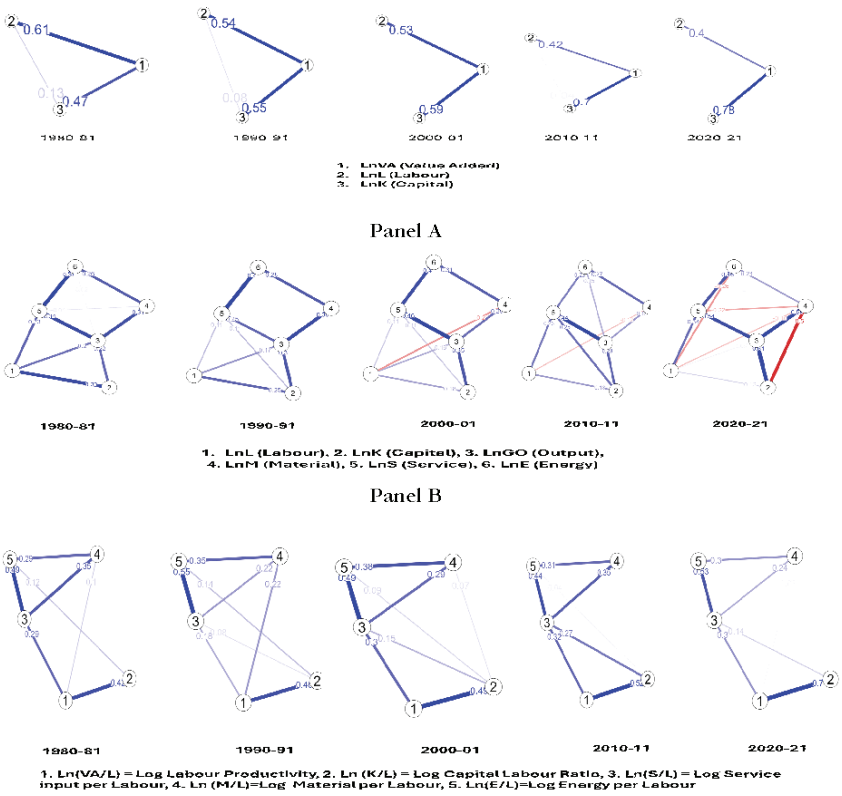
Note: See Table A1 (Appendix for detailed results.)

Further, we examine the long-run behaviour of value added, labour, and capital over the last four decades, using panel data from the KLEMS series of the Reserve Bank of India, covering 27 industry groups and 42 years. Appendix 1 provides the details of the estimation. Over the whole period, while capital reports a coefficient of .64, labour's coefficient is 0.55, summing a little above one and implying a slight inclination towards increasing return (Figure 2). While estimating these values, we provisioned for heterogeneity in parameters across industries. However, the strategy changes when we split the data into two parts: 1981-82 – 1999-00 and 2000-01 – 2022-23. Here, the short trend windows allow homogenisation of long-run parameters. In the first phase, the economy is inclined towards diminishing returns, with capital and labour elasticities of 0.58 and 0.19, respectively. Concerning the phase after 2000, the pattern exhibits higher coefficients for both labour (0.28) and capital (0.82). More succinctly, while the capital's stake is more prominent and increasing, the impact of labour is also growing. Although employment growth is stagnating, its effect remains crucial for the economy's development. The point of discernment is whether the expansion of labour is in volume or quality. Another essential aspect of our analysis is breaking

the time into two phases. The logic is that the year 2000 marks a new juncture, bringing new productive forces such as the Internet and software. Although this categorisation is not immune to bias, the year 2000 is undoubtedly in the vicinity of significant technological and globalisation-driven changes.

Figure 3

Labour and Economy: Structure and Relations



Source: KLEMS Database, Reserve Bank of India (RBI)

Note: The network of variables was computed using the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) estimator (Available with JASP statistical software)

The above analysis throws light on the emerging role of labour in the economy. While it is increasing in absolute terms, its relative position

to the capital has dropped. To explore further, we examine the changes in the relationship among labour, capital, and value added. To visualise the dynamics, we plot the networks of variables, using the Extended Bayesian Information Criterion Graphical Least Absolute Shrinkage and Selection Operator (EBICglasso) estimator (Isvoranu & Epskamp, 2023). It differs from regression models because its purpose is to explore interrelations rather than infer causal effects. It conveys how the relationships between variables vary over time, capturing the intensity and direction (positive or negative).

The analysis covers data for the beginning years of five decades: 1980-81, 1990-91, 2000-01, 2010-11, and 2020-21. Figure 3 shows three panels: A, B, and C. Panel A depict the structure of ties between labour, capital, and value added. Panel B covers the relationships among output, labour, capital, materials, energy, and service inputs. Panel C delineates the relationships among labour productivity, the capital-labour ratio, energy per labour, material per labour, and service input per labour. Panel A shows an interesting pattern. While the tie between labour and value added has steadily declined (from 0.6 to 0.4) over the last four decades, the pair of capital and value added has consistently increased (from 0.47 to 0.78).

The tie between capital and labour remained quite feeble. The merging story is that capital seems more crucial in shaping the direction of value creation in the Indian economy, especially in setting the terms of labour's relevance in future. The pattern of this sort raises curious questions, such as whether it holds when we explore the structure of the output, incorporating more dimensions like material, service input, and energy. Panel B illustrates the dynamics of the interrelationships among labour, capital, output, material and service inputs, and energy. Interestingly, the relationship between labour and production has been in a consistent decline, and it has virtually disappeared over the last two decades.

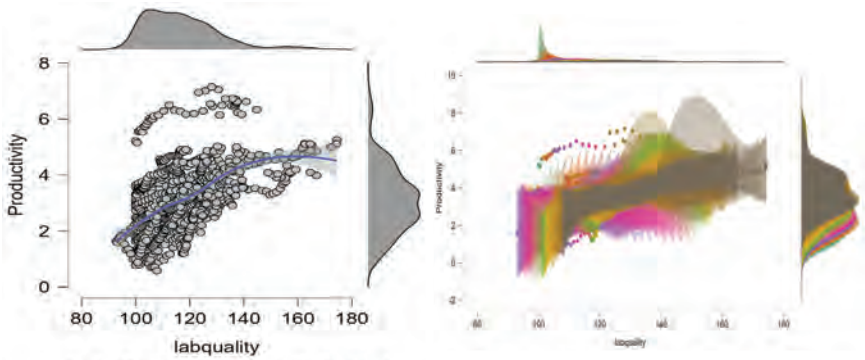
However, the link between capital and labour is more pronounced, despite a consistent decline from 0.33 to 0.12. Interestingly, service input is more aligned with labour. The strength of the tie is more visible in recent decades. Another noteworthy feature is that the tie between labour and capital has become negative. Over the last decade, capital has shown a discernible negative relationship with material. Perhaps the technology is turning out to be both labour- and material-saving. The service input is more central

to this structure, showing relatively higher centrality than other dimensions. The striking point in panel C is the relationship between labour productivity and the capital-labour ratio. It has been steadily increasing from 0.42 to 0.7. Another visible partner in labour productivity is service input (0.3 over the last decade). While the early decades show more coherent structures and dense ties among all the measures, the structure evolved into two triadic communities connected by a bridge of service inputs. One triangle consists of productivity, capital labour ratio, and service input per labour. The second one includes material, energy, and service inputs per labour. Service input labour is an integrating factor in the structure, increasing its centrality.

Two dimensions closely interact with labour productivity -Capital Labour Ratio and Service input per labour. Drawing on the efficiency wage hypothesis, human effort translates into productivity when rewarded appropriately. It's a wilful choice from Labour's side. In aligning productivity with production or service processes, the quality of labour appears to be more impactful than sheer labour quantity. We unravel the relationship between labour quality and labour productivity (Figure). The first figure presents pooled data without separating years.

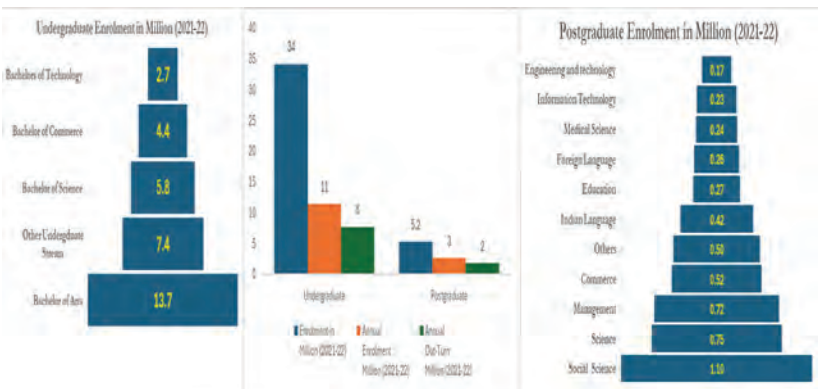
Overall, there appears to be a direct link between labour quality and productivity. The second part gives an ensemble of year-wise patterns (Figure 4). It also shows an apparent positive relation. While productivity is more bell-shaped over the years, labour quality is more inclined towards the lower values. Education and labour-market returns are the vital measures used to compute the quality index. This clearly indicates that a productivity-driven future economy cannot compromise on the quality of labour. Therefore, it is crucial to understand the role of education in the labour market, especially the impact of higher education on youth in India.

Figure 4
Productivity and Quality of Labour (1980-81 – 2022-23)



Source: KLEMS Database, Reserve Bank of India (RBI)

Figure 5
Enrolment, Annual Enrolment, and Out Turn in Indian Higher Education (in Million)



Source: Based on Government of India (GoI) (n. d), All India Survey on Higher Education 2021-22, Department of Higher Education, Ministry of Education.

3. Quality of Labour: Understanding Indian Higher Education

Concerning the quality of employment, higher education plays a pivotal role in fetching better labour market outcomes, such as formal employment and higher wages. Despite sustained investment efforts, the coverage of

eligible people in higher education, as measured by the Gross Enrolment Rate, remained around 28%, far short of potential. It implies that the supply of graduates will expand considerably in the future. Over the years, there has been a significant increase in the number of higher educational institutions (HEIs). Recent data shows that there are 1386 universities, 53306 colleges, and 16729 standalone institutions in India.[2]. The system caters to an enrollment of 43 million pupils. Of these, enrolment in undergraduate (UG) programmes is 34 million, while the postgraduate (PG) system has 5.2 million pupils (figure 5).

To gauge the flow of pupils into the system, we calculate annual enrolment by dividing total enrolment by the average stream duration. For the UG, it is three years, while it is five for the PG. The annual enrolment for UG and PG is 11 million and 3 million, respectively. Of the UG cohorts, 72% graduated, which is called the yearly turnout (8 million). For PG, it is two-thirds (2 million). Combining these two streams, the flow of successful cohorts is 10 million, forming a talent catchment of 20-23-year-old youth in India. In the case of UG, among enrolled pupils, two-fifths pursued an arts degree, primarily in the social sciences or languages, and a little above one-sixth were in the Science stream. Commerce accounts for 13%, and 9% pursued technology. One-fifth enrolled in other UG streams, including medicine, law, and business. The PG is more specialised than the UG. The social sciences alone account for 1 million enrolments, followed by science (0.75 million), management (0.72 million), and commerce (0.52 million), while language, medicine, and technology absorbed the rest. During 2017-18 – 2021-22, UG enrolment grew at a compound annual growth rate of 4%, while PG enrolment grew at 6%. Assuming the prevailing out-turn proportions and growth rates remain, the eligible talent pool after 10 years might reach 12 million for UG and 3.6 million for PG. The dynamics will result in an average annual increase of 0.6 million. This is a highly conservative projection, assuming a stagnant gross enrolment rate, slow expansion of institutional capacity, and static out-turn ratios.

The above analysis raises important questions. While the talent pool with higher education in a populous country is sure to grow over the next few

2 https://dashboard.aishe.gov.in/hedirectory/#/hedirectory, viewed on 17/12/2025.

decades, is it sustainable in assuring decent jobs and meaningful engagement opportunities for aspiring youth? Although the state has been envisioning transformative policies such as the National Educational Policy (NEP) 2020, the transition to impactful outcomes requires a creative approach to balance the quality of educational capacity with its reflection in value generation in the economy through labour markets.

There are two key institutional systems to gauge the quality of higher education in India: The National Assessment and Accreditation Council (NAAC) and the National Institutional Ranking Framework (NIRF). While NAAC evaluates the institutional progress in processes and outcomes over a five-year cycle, NIRF measures annual progress. Both institutions measure the quality of higher education. Despite the push from the Ministry of Education and regulatory bodies, only 8749 colleges attained NAAC accreditation (one-sixth of colleges in India).

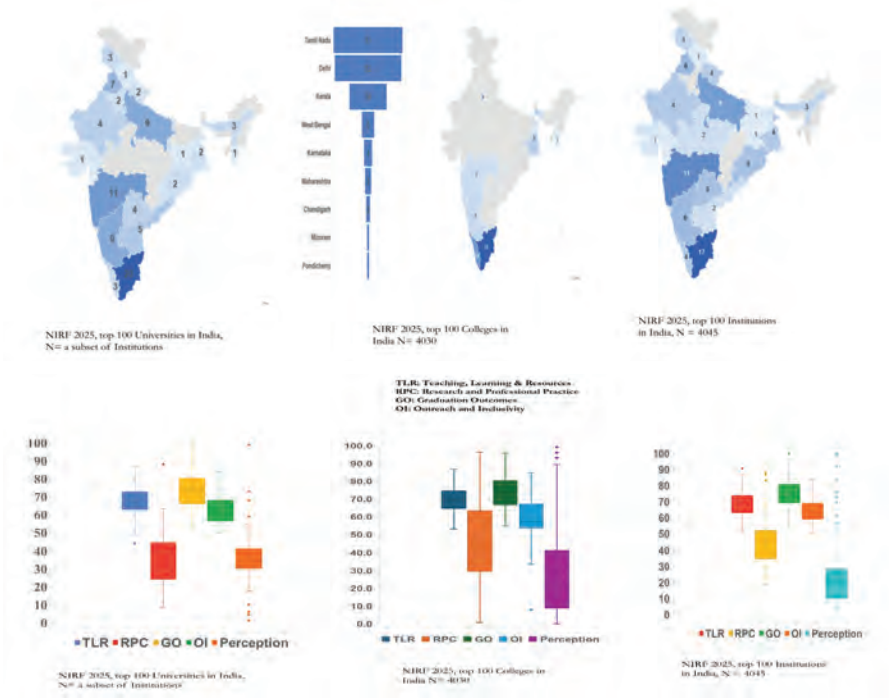
For universities, the number of accredited institutions is 573 (41%)[3]. It clearly shows that many colleges and universities lie outside the pool of certified institutions, and there's a severe quality deficit in higher education. NIRF is an annual measurement of outcomes. It measures five dimensions: teaching, learning and resources (TLR); research and professional practice (RPC); graduation outcomes (GO); outreach and inclusivity (OI); and perception. For universities and institutions, TLR and RPC weigh 30% each, GO's weight is 20%, and the remaining components carry 10% each. For colleges, TLR's weight is 40, followed by GO (25%). RPC carries 15 % weight. The other two weigh 10 % each. Ever since the inception of NIRF in 2026, it has been regularly publishing the institutional ranking. Moreover, it covers other professional domains, such as management. As shown in Figure 6, there are significant regional imbalances in the rank order of the top 100 institutions, particularly among colleges. Nearly 80 % colleges are in three states -Tamil Nadu, Delhi, and Kerala, while some of the bigger states do not have a single college featured in the list. The situation is better for the rank orders representing universities and institutions because many of them have a pan-India enrolment base. However, most colleges rely too heavily on neighbourhood talent pools. The puzzle here is: what fraction of students

3 https://assessmentonline.naac.gov.in/public/index.php/hei_public_dashboard, viewed on 23/12/2025

will pursue higher-quality universities, institutions, and colleges? The reality is that the quality is a scarce means, and inaccessible for a large chunk of learners.

Figure 6

National Institutional Ranking Framework (NIRF) 2025



Source: NIRF 2025 (https://www.nirfindia.org/Rankings/2025/Ranking.html)

Another critical component is the human resources in Indian higher education. There are 1.6 million teachers and 1.2 million non-teaching staff in the higher educational system. The pupil-teacher ratio is 24. Is this human resource-based approach impactful in meeting the scaling up and upgrading the quality in higher education? The bottom part of Figure 2 unravels the range of variation in outcomes for colleges, universities, and institutions. While TLR, GO, and OI are relatively standardised, showing much less variation, RPC stands in contrast, with a wider margin and a lower threshold value. It generates the highest variability in the rank order. Although it has just 10% weight, perception behaves like RPC. It means that even in the top cluster,

very few institutions coherently generate research and impactful learning. NIRF or NAAC are not beyond critical assessments. These institutions have room for further improvement. Nevertheless, the above patterns point to visible skewness in the supply side of higher education. If this structure remains stable over the years, it creates serious disadvantages for the talent pool.

4. Labour Market of Graduates and Postgraduates

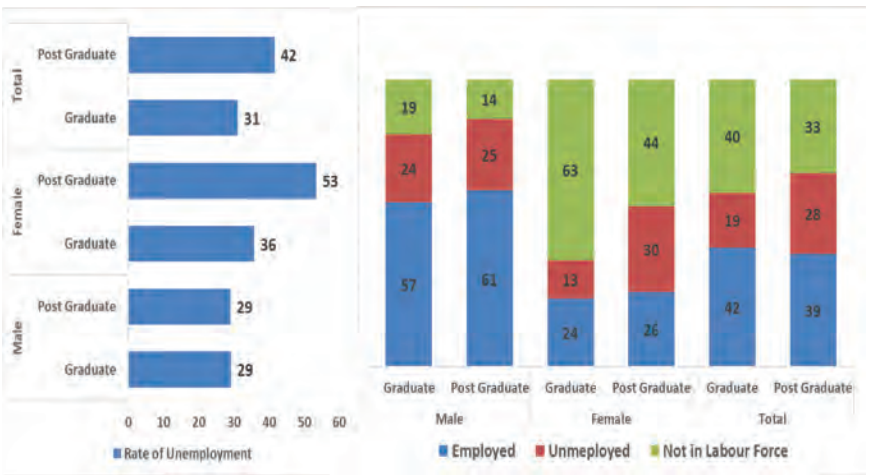
It is crucial to examine the opportunities for the talent pool in the labour market. We restrict our analysis to graduates and postgraduates in the 22-27-year age group. Using the periodic labour force survey (PLFS) 2022-23, we pool all persons whose highest educational attainment is either graduation or post-graduation—the 5-year window accounts for the search period for an employment opportunity, covering wage and self-employment. While 42% of graduates are employed, 19% are unemployed, and the rest are not in the labour force (40%) (Figure 7). Among postgraduates, the employment share is 39%, 28% are unemployed, and one-third are not in the labour force. This pattern is sensitive to gender. Among graduates, women make up a little less than two-thirds who are not in the labour force. However, the share of women postgraduates not in the labour force plummets to 44%. On the other hand, unemployment is proportionately lower for graduate women (13.5%) than for postgraduates (30%). Similar employment absorption rates prevail for women graduates (26%) and postgraduates (26%). In contrast, men report much higher employment rates for graduates (57 %) and postgraduates (61 %), while showing similar unemployment proportions (24 % for graduates and 25 % for postgraduates). Not in the labour force is another point of contrast. The figures for graduates and postgraduates are 19% and 14%, respectively.

The unemployment rate, defined as the ratio of the labour force to employment, is another vital indicator that reflects the quality of labour market outcomes. It ranges from 29% (Male graduates and postgraduates) to 53% (women postgraduates). For women graduates, it is 36 %. Combining men and women, the rate for graduates is 31%, and for postgraduates, 42%. These patterns clearly point to a quality gap in the production of human resources by Indian higher education. Our previous analysis complements

it. For the UG system, there is negligible diversification in course enrolment. Nearly two-fifths pursued an arts degree. The question is whether these academic pursuits meet the industrial requirements. A similar vacuum is evident for the PG, as well. The leakage in the system works this way: out of 8 million eligible UG and PG, only 3 million might be inducted into the labour market.

Figure 7

Labour Market Composition (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)



Source: Computed from the unit records of Periodic Labour Force Survey 2023-24

While attaining employment is a desirable outcome, it is not immune to a quality assessment. A significant concern is whether it generates a decent wage or earnings. Broadly, employment is of three types: self-employment (SE), regular wage employment (RE), and casual employment (CE). Further, SE consists of own account work (OW), employer (EM), and helper (HL). OW is a scenario of self-ownership and self-working in a production or service system, such as a small farm, street vending, or a petty business unit.

EM involves owning micro-, medium-, or larger-sized units while employing others. HL is rendering paid or unpaid effort to run the family-based enterprise or units. Drawing cues from the data and the literature, except EM, OW and HL do not provide immunity from working poverty and sustained precarity. These streams -OW and HL- are more likely to be

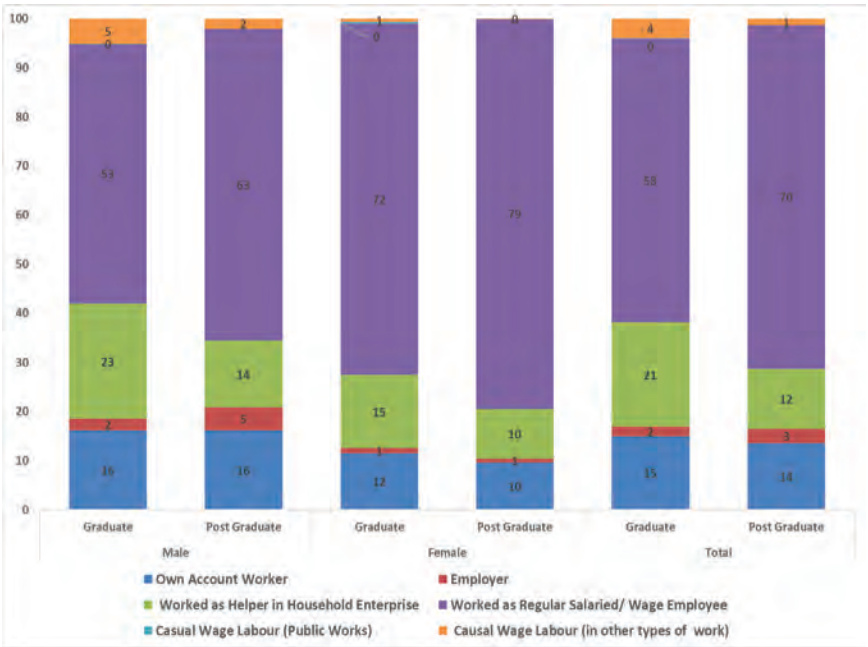
'low-hanging fruit' for job or livelihood seekers. However, there are a few exceptional people who begin from these points and rise to become fortune-makers. And these progressive transitions are relatively uncommon.

The RE is either a formal or an informal contract that assures wages. A formal RE carries wages, social security and employment rights, while an informal type provides only wages. A job in government or establishments like a public limited firm is an example. In the case of an informal kind, contract jobs are examples. The CE is an uncertain opportunity, almost like an arm 's-length contract. In this case, the labour has a paid engagement now, but not necessarily in the immediate future, and this is the low-lying opportunity, paying the lowest. Across the spectrum, EM and RE are the most lucrative opportunities.

Very few pursue EM, since it is more legacy-dependent in the Indian context or elsewhere, or requires a risk appetite. Barring EM, formal RE emerges as the most gainful and sought-after opportunity. It provides more job security, better entitlements, higher pay, and growth prospects. Therefore, it is more competitive. There are entry barriers to hiring candidates for the job. Qualification and ability are two primary criteria for hiring, and the former serves as the threshold. The qualification is a certified threshold, such as a degree, provided by a higher educational institution. Although the certification does not necessarily ensure ability, it serves as an influential signal in competitive hiring, especially when reliable information about the candidate's ability is available.

For the youth who attained higher education, formal RE is a natural destination. Do they achieve the desired outcomes, such as formal jobs in India? The recent data show that RM accounts for 70% and 58% for UG and PG, respectively (Figure 8). However, the share of EM is too low (2% for UG, 3% for PG). The HL forms 21% and 12% for UG and PG, respectively. The casual employment CE forms a minuscule share for UG and PG streams. Interestingly, RE is the principal employment for PG women (79%), while 72% of UG women are in RE. Nearly one-tenth of PG women are in HL, supporting familial enterprises. For UG women, the share of HL is 15 %. For men, the shares of RE are 53% and 63% for UG and PG, respectively. In the UG stream, 23 % are in HL. This is a serious concern. The question is how this category of youth upgrades to more gainful opportunities.

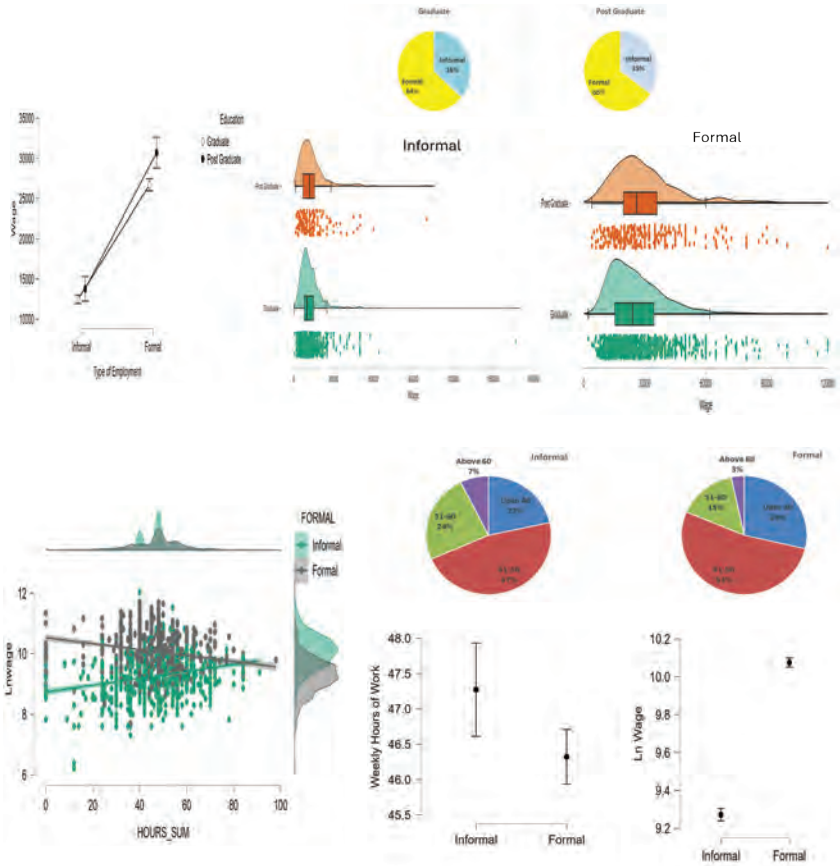
Figure 8
Type of Employment (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)



Source: Computed from the unit records of Periodic Labour Force Survey 2023-24

There is a massive wage gap between formal and informal jobs. The gap in average wages between formal and informal employment exceeds 100%, generating an enormous premium for both UG and PG in formal employment relative to informal employment. The distribution graphs show a concentration of lower values for informal jobs, while the formal stream shows lower skewness. Another glaring disparity is in working hours (Figure 9). Informal jobs exhibit a positive relationship between hours of work and wages, whereas formal employment shows a negative relationship. On average, informal workers work an hour more per week than formal workers. In the case of informal employment, nearly 31% of persons work more than 50 hours per week. In contrast, in formal jobs, only 18% work more than 50 hours.

Figure 9
Wage, Hours of Work, and Type of Employment



HOURS_SUM = Weekly Hours of Paid Work,
Lnwage = Log Monthly Wage

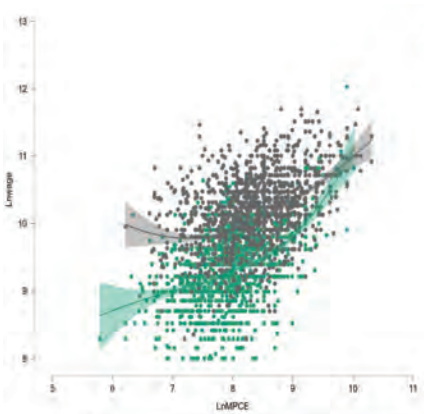
Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

Regarding Indian youth who have attained higher education, an intriguing question is what translates into a decent wage and formal employment. Does it rely on ability? It is hard to get data on ability. However, we pose alternative questions, such as whether legacy factors, like household consumption, play a role. Compared to the informal segment, the formal segment follows a higher trajectory of household consumption and wages (Figure 10). Very clearly, irrespective of the type of employment, household consumption,

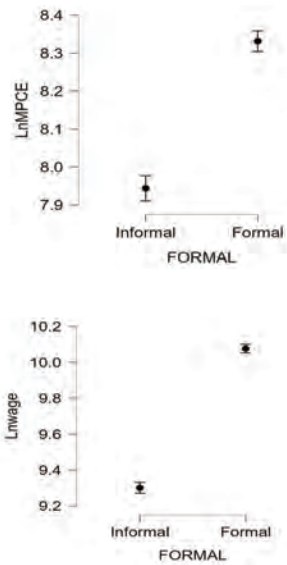
a proxy of economic well-being, translates into a higher average salary. Moreover, the pattern prevails across the percentiles. This evidence also intersects with social categories -Scheduled Tribe (ST), Scheduled Caste (SC), Other Backwards Classes (OBC), and others. The figure 11 delineates a direct relation between household consumption and wage across social categories.

Figure 10

Wage, Monthly Per Capita Consumption Expenditure, and Type of Employment



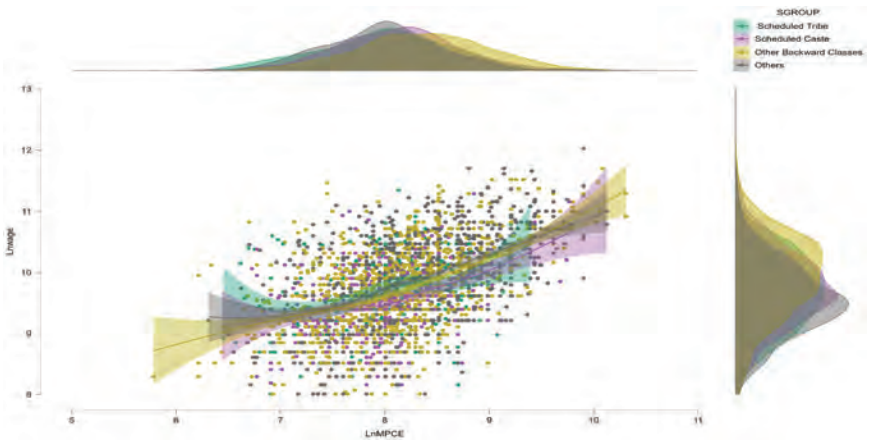
	LnMPCE		Lnwage	
	Informal	Formal	Informal	Formal
Valid	1233	1907	1233	1907
Missing	0	0	0	0
Mean	7.944	8.331	9.301	10.076
Std. Error of Mean	0.017	0.014	0.016	0.012
Std. Deviation	0.596	0.605	0.548	0.532
Minimum	5.784	6.215	8.006	8.294
Maximum	10.021	10.309	12.026	11.995
20th percentile	7.438	7.824	8.854	9.616
40th percentile	7.824	8.187	9.210	9.903
60th percentile	8.086	8.506	9.393	10.225
80th percentile	8.412	8.819	9.711	10.490



Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)
Lnwage = Log Wage, LnMPCE=Log Monthly Per Capita Consumption Expenditure

Figure 11

Wage, Monthly Per Capita Consumption Expenditure, and Social Category



Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)
Lnwage = Log Wage, LnMPCE=Log Monthly Per Capita Consumption Expenditure

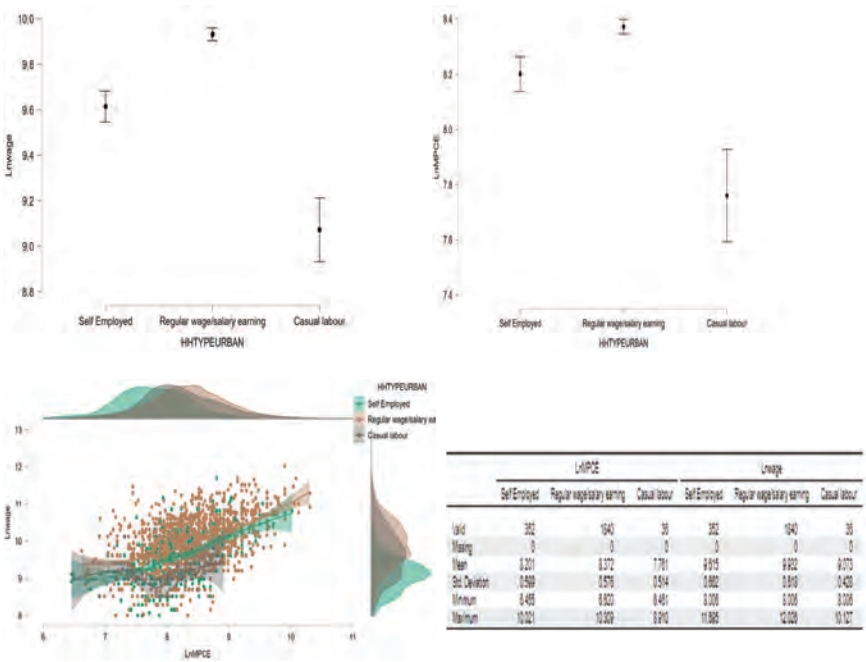
Another interesting dimension is the type of household, and it is based on the head of household's employment. Regarding the urban population, there are three categories: self-employed, regular wage-earners, and casual workers. For the rural, there are five categories: self-employed in agriculture, self-employed in non-agriculture, regular wage, casual in agriculture, and casual in non-agriculture. Figure 12 shows that consumption and salaries vary by household type, whether urban or rural. Youth who have attained higher education are not immune to the effects of household background on labour market outcomes.

For the urban area, graduates and postgraduates from households headed by a person in regular wage employment report substantially higher average wages than those in other self-employed or casual-employed households. While the cohorts from regular employed households report the highest wages, the self-employed households come next, and those with casual employment show the lowest. The same pattern holds for consumption expenditure as well. The pattern for the rural area also puts the regular wage as the category with the highest consumption and wage. However, the hierarchy in consumption does not iso-morph to the salary.

For consumption, the order has the household with regular employment at the top, followed by self-employment (non-agriculture), casual employment (non-agriculture), casual employment (agriculture), and self-employment (agriculture) at the bottom (Figure 13). However, it does not replicate for the wage. Concerning wages, the category of regular salary is at the top, followed by self-employed (non-agriculture), self-employed (agriculture), casual (non-agriculture), and casual (agriculture). The big question here is whether higher education is a transformative process. If it does transform, there must be discernible reflections from the outcomes, such as wages.

Figure 12

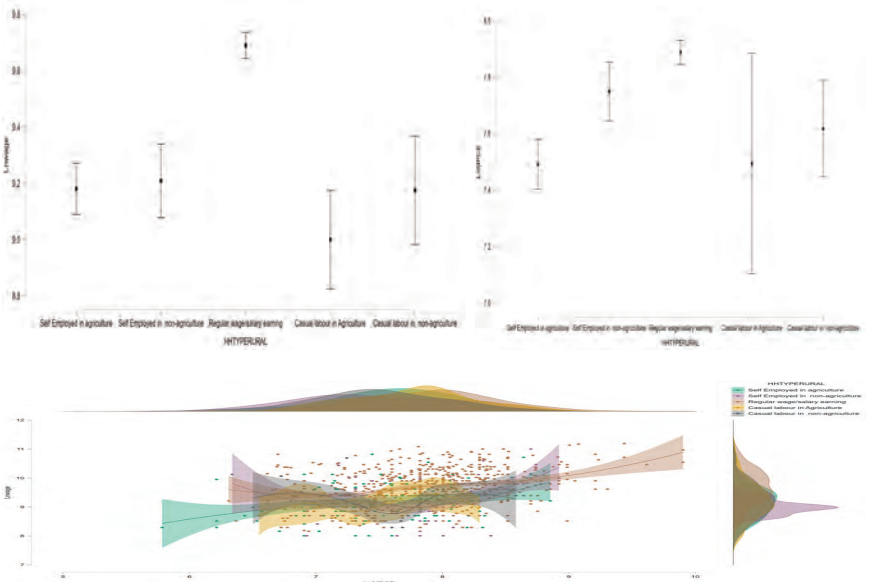
Wage, Monthly Per Capita Consumption Expenditure, and Type of Household (Urban; HHTYPERURAL)



	LnMPCE			Lnwage		
	Self Employed	Regular wage/salary earning	Casual labour	Self Employed	Regular wage/salary earning	Casual labour
Valid	352	1940	38	352	1940	38
Missing	0	0	0	0	0	0
Mean	8.201	8.372	7.791	9.615	9.802	9.073
Std. Deviation	0.569	0.579	0.514	0.882	0.910	0.420
Minimum	6.455	6.823	6.451	6.208	6.208	8.006
Maximum	10.021	10.309	8.910	11.995	12.206	10.127

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)
Lnwage = Log Wage, LnMPCE=Log Monthly Per Capita Consumption Expenditure

Figure 13
Wage, Monthly Per Capita Consumption Expenditure, and Type of Household (Rural; HHTYPERURAL)



	LnMPCE					Lnwage				
	Self Employed in agriculture	Self Employed in non-agriculture	Regular wage/salary earning	Casual labour in Agriculture	Casual labour in non-agriculture	Self Employed in agriculture	Self Employed in non-agriculture	Regular wage/salary earning	Casual labour in Agriculture	Casual labour in non-agriculture
Valid	147	89	637	9	30	147	89	637	9	30
Missing	0	0	0	0	0	0	0	0	0	0
Mean	7.491	7.749	7.888	7.494	7.617	9.100	9.200	9.990	8.999	9.175
Std. Deviation	0.547	0.501	0.555	0.590	0.474	0.584	0.629	0.691	0.268	0.540
Minimum	5.704	6.307	6.310	6.551	6.502	8.006	8.006	8.161	8.613	8.294
Maximum	8.954	9.503	9.903	8.294	9.392	10.820	11.002	11.191	9.457	10.602

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)
Lnwage = Log Wage, LnMPCE=Log Monthly Per Capita Consumption Expenditure

The previous analysis generates greater curiosity about whether higher education is a catalyst for transition in the labour market for youth. We cross-tabulate rural and urban household types with labour force participation and employment type (Figure 14). For instance, we examine the likelihood that a youth from a rural agricultural casual-employment household moves into regular wage employment. Similarly, we assess whether youth from the regular wage employment category in urban areas tend to be absorbed into the same category.

Figure A shows that outcomes vary across rural household types. Among self-employed agricultural households, only 37% of young graduates and postgraduates are employed, while the shares of not in the labour force and unemployed are 44% and 19%, respectively. For non-agricultural self-employed households, the share of employment is slightly higher (41%), while the proportion of unemployment is higher (23%). However, compared to the first category, the share of those not in the labour force is lower (37%).

In regular wage households, employment participation is 45%, the highest among the categories, while unemployment is the lowest (18%). The category 'casual labour in agriculture' reports the lowest employment participation among young graduates and postgraduates (26 %) and the highest unemployment rate (42 %). However, non-agricultural casual labour households report a better employment and unemployment situation, with rates of 34% and 25%, respectively. Figure B is about the urban household. For this group, regular-wage households also report the highest employment rate (55%) and the lowest unemployment rate (15%). Self-employed households report 39% employment participation, the highest not-in-labour-force proportion (42%), and an unemployment proportion of 19%.

The casual wage category reports the highest unemployment and the lowest employment percentages, 30 and 31, respectively. Figures C and D show the employment status of young graduates and postgraduates belonging to rural and urban households. In rural areas, educated youth from self-employed households show an evident proclivity to pursue self-employment, while a few join regular employment. Just 1% of youth from self-employed agricultural households become employers, while 55% are helpers in family concerns.

The share of own account work is 21%. From this category, only a fifth pursue the regular wage employment. For non-agricultural self-employed households, employers' share is 5%, while own-account work accounts for 42%. The share of helpers is 29% in this category, and regular wage employment accounts for 23%. Regarding the regular wage group, a whopping 84% of young graduates and post-graduates remain in regular wage employment. Only 2 % are employers. Nearly two-thirds of educated youth from agricultural casual workers' households end up in casual work, while 22 % are in regular wage employment. However, in the non-agricultural casual work segment, regular wage employment accounts for 32%, and the share of casual work is 57%. For the urban, 95% of young graduates and

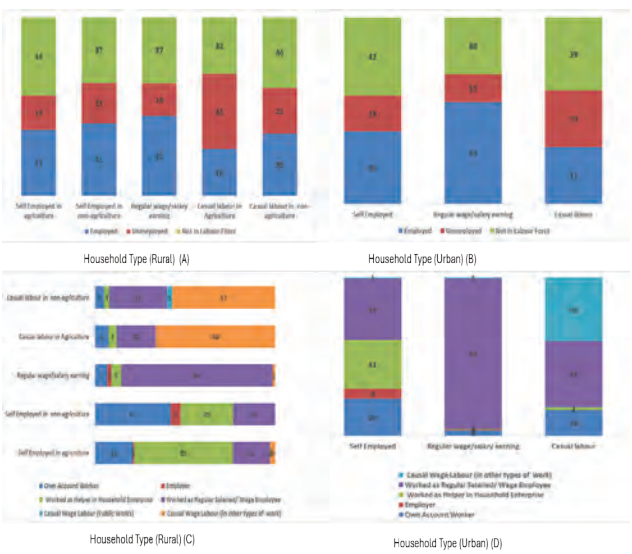
postgraduates from regular wage households are employed in the same stream.

In contrast, the self-employed category is diverse, with 61% self-employed and 39% on a regular wage stream. An interesting pattern is that 6 % are employers. However, 31 % are helpers in familial establishments. Own account work forms 21 %. Among casual labour households, 40% of educated youth are in casual employment. However, 42% are in regular wage employment, and 16% are in own-account work. There is negligible diversification among regular-wage households, especially in urban areas.

It appears that young graduates and postgraduates find this stream more fulfilling in terms of wages and entitlements, and therefore, there is no incentive to become self-employed. Moreover, self-employment streams, such as own-account work and helpers, do not provide safeguards against precarious working and living conditions. Becoming an employer requires either a family legacy or a will to participate in risky ventures.

Figure 14

Household Type and Employment Status Young graduate and postgraduates



Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

5. Assessing the impact of Higher Education on the Labour Market

It is crucial to assess whether employed young graduates and postgraduates (the second group) have an advantage in securing regular wage employment over employed young cohorts (the first group) who have not yet attained any form of higher education. Both groups are in the 22-27 age group. We conduct a Bayesian A/B test to determine whether the first group has an edge over the second in securing regular employment (Hoffmann et al, 2022). According to the test, if the second group gains, the log-odds ratio is greater than 1. As shown in the figure, we conducted the test across all household types (Table 1).

Across these types, young people who attained higher education convincingly outperform the other group in achieving regular wage employment. However, the log odds of securing regular wage employment vary across household types. It ranges from 0.35 (urban regular) to 41.16 (urban casual wage) (Figure 15). Among rural households, the rural non-agricultural causal work category has the highest odds (log odds = 4.14), and the regular wage employment category has the lowest (log odds = 1.3). Compared to urban self-employment households (log odds = 1.24), the rural agricultural and non-agricultural self-employment streams report higher log odds (2.32 and 2.33, respectively).

Table 1
Design of Bayesian A/B Test

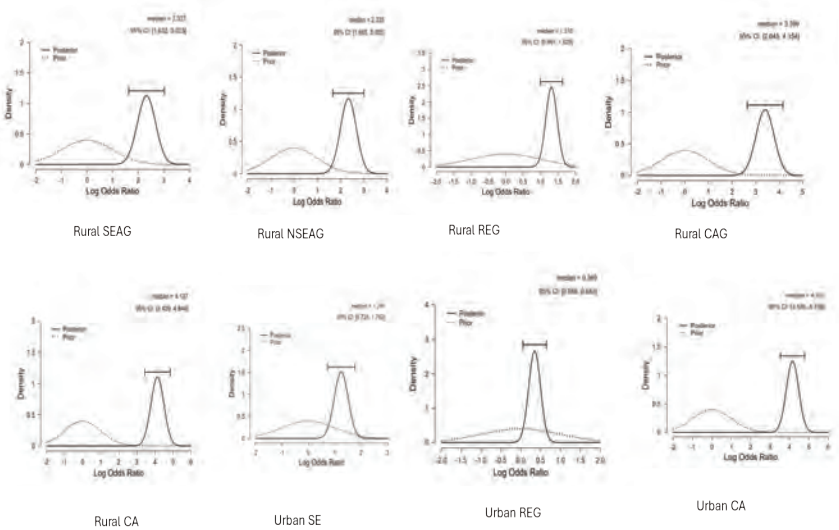
Definition of Groups	Group 1 22 ≤ Age ≤ 27, Education upto Higher Secondary (Employed)		Group 2 22 ≤ Age ≤ 27, Education upto Higher Secondary (Employed)	
Type of Household	Percentage attained Regular Wage Employment	Sample Size	Percentage attained Regular Wage Employment	Sample Size
Rural Household				
Rural Self-Employment in Agriculture	7.3	3917	21.6	727
Rural Non-Agricultural Self-Employment	8.6	1885	24.5	379
Rural Regular Wage Employment	69.2	2076	87.9	743
Rural Casual Employment in Agriculture	8.6	783	19.2	52
Rural Casual Non-Agricultural Employmen	5.3	1991	31	116
Urban Houshold				
Urban Self-Employment	19	1971	37.2	1007
Urban Regular Employment	87	2641	93.7	2005
Urban Casual Employment	14	849	48.7	76
Total Sample		16113		5105

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24

The results indicate that the higher has the potential to catalyse transformative change in the lives of households, especially the poorer segment, in both urban and rural India. Although higher education carries a higher risk of unemployment, it increases the likelihood of securing regular wage employment, which is the gateway to formal, higher-paying jobs. The transition potential to a better labour market outcome is ostensibly clear in the case of casual work households, who occupy the bottom strata of the economic well-being. Therefore, education as a public good still has the potential to transform lives, provided it improves in quality and relevance.

Figure 15

Bayesian A/B test for attainment of regular salary/wage employment and type of Rural and Urban Households



Rural SEAG = Rural Self-Employment in Agriculture, Rural NSEAG = Rural Non-Agricultural Self-Employment, Rural REG = Rural Regular Wage Employment, Rural CAG = Rural Casual Employment in Agriculture, Rural CA = Rural Casual Non-Agricultural Employment, Urban = Urban Self-Employment, Urban REG= Urban Regular Employment, Urban CA = Urban Casual Employment

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Employed Non-Graduates (Group 1) and Employed Graduates and Post-graduates (Group 2) (set 2), 22 ≤ Age ≤ 27, 2023-24)

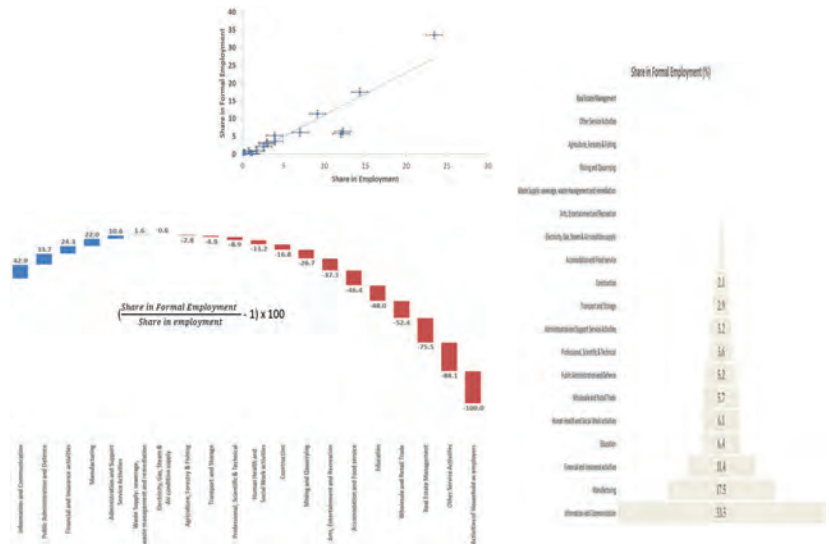
An important question is, where do jobs originate for young graduates? While it signifies the quantity of Jobs, another crucial dimension is quality and its relation to quantity. Broadly, in the Indian labour market, covering all ages and educational attainments, the volume of jobs and their availability may not be directly linked. For instance, while sectors like agriculture, construction, and private households are principal job creators, the formal jobs are scarce in these activities. However, this is not the case with the young graduates and post-graduates. For this segment, there is visible correspondence between employment creation and the availability of formal employment.

Figure 16 provides clear evidence of a direct relationship between the industry's share of jobs and its share of formal employment. The classic case is information and communication. Its share of jobs is 23%, and it accounts for 34% of formal employment. We compute an indicator as the ratio of the industry's share of formal employment to its share of jobs, then subtract one from it and express the number as a percentage. Interestingly, the information and communication sector scores 43%. It means the increase in formal job sharing is 1.43 times the sector's employment share.

A little more than one-sixth of formal jobs come from the manufacturing sector, while its share in employment is 14%, generating an incremental factor of 22% towards the share of formal jobs. Another interesting case in point is financial and insurance activities. While its share of employment is 9%, it creates 11% of formal employment. In contrast, trade's share in employment is 12%, while its share in formal employment is just 6%, resulting in a decrement factor of 52%. Education also reports a 48% decrease. Its share in employment is 12%, and it accounts for 6% of formal employment.

The analysis reveals that information communication, manufacturing, and finance offer scope for a decent pool of talent for higher education, provided the higher education system generates a human resource pool that matches industrial requirements.

Figure 16
Share of Industry in Formal Employment

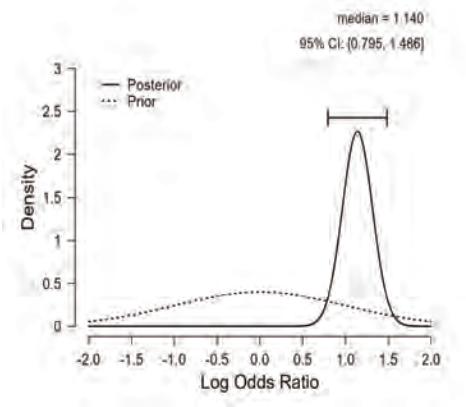


Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

Note: See Table in Appendix 2 for more data.

Does the current state of Indian higher education meet industry's needs? Industries generating decent formal jobs, such as information and communication, or manufacturing, rely on new technologies. At the same time, early in the 40% of enrolments in the undergraduate streams pursue Bachelor of Arts degrees. In this context, it is critical to examine whether technical qualifications matter for getting formal jobs. We apply Bayesian A/B analysis to assess this question. We identify two groups from the data. While one is without any technical qualification, the second group has one. Figure 17 delineates the results. The posterior inference points to a robust inclination towards favourable odds, implying that the technical qualification is indispensable for getting formal jobs. Although the National Education Policy 2020 envisions a multidisciplinary, credential-oriented system, the question is how the system adapts to change.

Figure 17
Technical Qualification and Formal Employment



	Formal Employment (%)	Sample Size
No Technical Qualification (Group 1)	54	2192
Having Technical Qualification (Group 2)	74	970

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

6. Unemployment and the search for a job

Despite a higher likelihood of securing a formal job, the unemployment rate remains relatively high among young graduates and postgraduates in India. The crucial question for a labour market's sustainability is how long unemployment endures. How do unemployed youth search for an opportunity? As shown in Figure 18, nearly one-third of the unemployed are in the category of unemployment spell from 1 to 2 years, while 11.6 % might endure a spell of more than 5 years. Almost one-third of the spells are up to a year, and one-fifth are between 2 and 3 years.

The longer the spell of unemployment, the greater reliance on formal channels, such as directly applying to job advertisements; it rises from 52% (up to 6 months) to 67% (more than 5 years). The reverse holds for informal routes, such as seeking help from relatives or friends. Another channel is the employment exchange; it goes up with the duration of unemployment (6 to 14 per cent). The pattern points to the significance of strengthening formal job-search channels through industry-higher-education-employment exchange collaborations, by creating more labour market intelligence on skills, job availability, industrial expectations, and learning through internships.

Figure 18
Duration of Unemployment and Job Search

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

7. Participation in the Green Economy

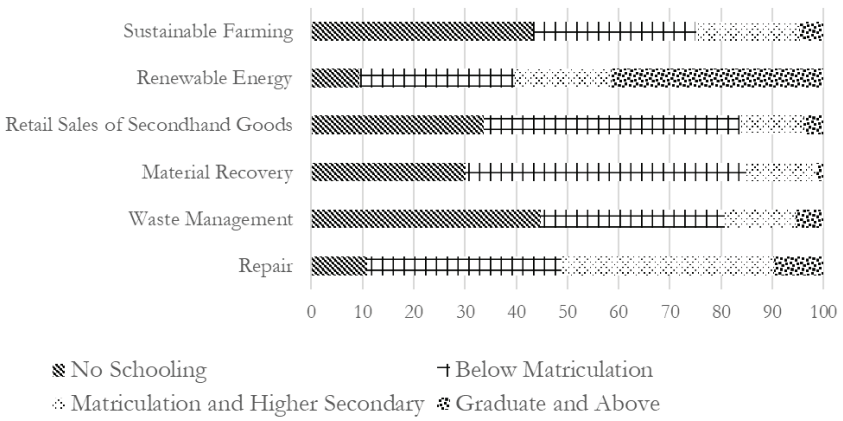
Another vital question is about the participation of graduates and post-graduates in green activities. Appendix 3 provides a detailed classification of green activities. Broadly, based on the logic of the circular economy, the green activities include waste management, renewable energy, and sustainable farming. Nearly 3 % participate in green activity-based employment, totalling approximately 0.4 million (Figure 19). Out of this, the vast majority is in sustainable agriculture (79 %), and one-sixth are engaged in repair and other activities; the remaining are renewable energy (3.6 %) and waste management (1.6 %). In renewable energy, the largest share of the workforce attained higher education (Figure 20). The low participation of graduates in green employment is due to limited formal employment opportunities (Bino, 2023). Another reason could be the weak linkage between higher education and the industrial and business system of the circular economy. There is considerable potential in interlinking higher education and the circular economy. Upgrading small and medium-sized firms operating in the sector and aligning them with

the higher education system might be pivotal to linking sustainability and transition jobs for educated youth.

Figure 19
Participation in Green Employment

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)
See Appendix 3 for the classification of green economic activities.

Figure 20
Green Employment and Educational Attainment (%) (15 Years and Above)



Source: Bino (2023)

8. Conclusion

The trends of the last four decades clearly indicate that capital is consolidating its centrality in the Indian economy, while labour's stake is on a visible drop. Despite it, labour remains pivotal to sustainable and inclusive growth. Education is clearly a catalyst for aligning human power with the economic system's potential. While schools and higher education systems play crucial roles, higher education is more closely linked to labour market outcomes. If higher education is slow to realise this, there will be serious gaps in the youth's potential to create economic value. Based on our previous discussion, we identify scenarios for value creation and highlight where we lose and do not harness value (Table 2). If all who enrolled in the system complete the education and engage in a job or any value creation process that generates value equivalent to the living wage (say Rs 30,000 per month), the estimated potential from single-year graduates and postgraduates is Rs 5 lakh crore (more than 1 % of India's Gross Domestic Product). However, there is a leaky pipe here. Nearly one-third of undergraduate enrolment fails to complete the programme, while 30 % do not attain post-graduation. Perhaps, even if they fail to clear the programme, they might create value if flexible streams of learning exist. This is a point for higher education to transform learning opportunities by nearly fully realising its potential.

Table 2

The value of higher education: a framework

Streams	Under Graduate	Post Graduate	Total	Annual Value Creation if the average monthly wage/earning is Rs 30,000 (Rupees Crores)	Loss to the Economy (Rupees Crores)	Potential to improve
Annual Enrolment (million)	11.0	3.0	14.0	504000	Maximising Potential	
Successful Completion (million)	8.0	2.0	10.0	360000	144000	The Higher Educational System
Employed (Average for 22-27) (million)	3.4	0.8	4.1	149040	210960	More Diversity and Inclusion and Better Labour market intelligence
Regular Wage Employment (million)	1.9	0.5	2.5	89813		Upgrading of Small and medium enterprises
Formal Employment (million)	1.2	0.3	1.6	57284		Blending Technology with higer education

Source: Author's creation

Another missing link is the unemployment and those not in the labour force. Mostly women face it. Here, two dimensions are essential: diversity and inclusion and labour market intelligence. The state needs to implement

proactive policies that incentivise firms to be more inclusive in their hiring practices. Gender and social barriers affect the fluid flow of the employment system. While legislation has its benefits, incentives also have the potential for a transformative change. Despite the challenges, higher education offers hope for the poorest in society—the analysis shows. A noteworthy pattern is that cohorts from casual work households show a higher propensity for positive labour market transitions, while legacy still affects labour market outcomes in India. Another critical gap is the lack of alignment between higher education and new technologies. Although the National Education Policy (NEP) 2020 envisages a transition from a traditional disciplinary orientation to multidisciplinary systems, the change is in a formative stage. Alongside the policy, it is crucial to have a sustainable investment system to support a transformative higher education system. There is no visible participation by the higher education system and universities in India's circular economy. While it is an emerging opportunity, there is more to explore for aligning youth from the higher education system with active participation in it. Although productivity has strong links to the quality of labour and education, Indian higher education exhibits an apparent disparity in the quality of outcomes. There are very few centres of excellence, and a large majority of institutions struggle to balance quality and enrolment.

Appendix 1

Value Added, Capital and Labour: Long-run and short-run relationship

	Independent Variable	Coef.	Std.Err.	z	P>z	Min.	Max
Dependent Variable: Δ LnVAit						95 % Confidence Interval	
1980-1981 - 2022-23 (Mean Group)							
Long-run Effects	LnL	0.55	0.18	3.12	0.00	0.20	0.89
	LnK	0.64	0.06	10.16	0.00	0.51	0.76
	Error Correction	-0.32	0.03	-9.56	0.00	-0.38	-0.25
Short-run Effects	Δ LnL	0.06	0.11	0.51	0.61	-0.16	0.27
	Δ LnK	0.28	0.11	2.48	0.01	0.06	0.51
	Contant	-0.04	0.57	-0.07	0.95	-1.15	1.07
1980-1981 - 1999-2000 (Pooled Mean Group)							
Long-run Effects	LnL	0.19	0.05	3.69	0.00	0.09	0.29
	LnK	0.58	0.03	22.75	0.00	0.53	0.63
	Error Correction	-0.29	0.06	-4.51	0.00	-0.41	-0.16
Short-run Effects	Δ LnL	-0.15	0.24	-0.64	0.53	-0.61	0.31
	Δ LnK	0.47	0.13	3.7	0.00	0.22	0.71
	Contant	0.71	0.15	4.67	0.00	0.41	1.01
2000-2001 to 2022-2023 (Pooled Mean Group)							
Long-run Effects	LnL	0.28	0.06	4.74	0.00	0.17	0.40
	LnK	0.82	0.02	35.22	0.00	0.77	0.86
	Error Correction	-0.20	0.04	-5.67	0.00	-0.27	-0.13
Short-run Effects	Δ LnL	0.21	0.18	1.19	0.24	-0.14	0.56
	Δ LnK	0.30	0.15	2.01	0.04	0.01	0.59
	Contant	-0.22	0.05	-4.13	0.00	-0.33	-0.12

Note: LnVA = Natural Log of Real Value Added (2011 prices), LnL= Natural Log of Employed, LnK=Natural Log of Real Capital (2011 prices), Δ = Variable – Variablet-1, Estimation is based on Blackburne & Frank (2007), Pedroni (2001), and Pesaran et al (1999)

Panel Setting: 27 industry groups and 42 years.

Source: based on KLEMS database, Reserve Bank of India (1980-81 to 2022-23)

We used the Im–Pesaran–Shin (IPS) test for gauging the stationarity of the panel data. The null hypothesis of the test is that each panel has a unit root, implying that the data are nonstationary. The alternative hypothesis is that some panels are stationary. The test was performed using the Stata command xtunitroot. The test was applied to the whole data series (1980-81 – 2021-22), and to the series for 1980-81 – 1999-00 and 2000-01 - 2021-22. While LnVA is stationary across all three windows, LnL and LnK are

nonstationary. Using the following procedure, we cointegrate the stationary and nonstationary data.

To cointegrate the series, we use the Panel ARDL (Autoregressive Distributed Lag) method to estimate long-run and short-run relationships in panel data. The Stata command xtmpg computes it. If the parameters are homogeneous across the panel, we stick to the pooled mean group (pmg). On the other hand, if parameters are heterogeneous across panels, the mean group (mg) is more appropriate. To determine whether mg and pmg differ, we use the Hausman test. The null hypothesis is that the pmg is the ideal pick, while the alternative hypothesis points to the mg.

Stata Code for the cointegration.

For the period 1980-81 – 2022-23:

x*tmpg d.LnVA d.LnL d.LnK, lr(l.LnVA LnL LnK) pmg replace*

estimates store pmg

xtpmg d.LnVA d.LnL d.LnK, lr(l.LnVA LnL LnK) mg replace

estimates store mg

hausman mg pmg, sigmamore

For the period 1980-81 – 1999-00:

xtpmg d.LnVA d.LnL d.LnK if trend <= 20, lr(l.LnVA LnL LnK) pmg replace

estimates store pmg

xtpmg d.LnVA d.LnL d.LnK if trend <= 20, lr(l.LnVA LnL LnK) mg replace

estimates store mg

hausman mg pmg, sigmamore

For the period 2000-01- 2022-23:

xtpmg d.LnVA d.LnL d.LnK if trend > 20, lr(l.LnVA LnL LnK) pmg replace

estimates store pmg

xtpmg d.LnVA d.LnL d.LnK if trend > 20, lr(l.LnVA LnL LnK) mg replace

estimates store mg

hausman mg pmg, sigmamore

Appendix 2

Industry, Share in Employment and Formal Employment

Activity	Share in Employment	Share in Formal Employment
Agriculture, Forestry & Fishing	0.1	0.1
Mining and Qauarrying	0.2	0.2
Manufacturing	14.3	17.5
Electricity, Gas, Steam & Air condition supply	0.7	0.7
Waste Supply: sewerage, waste management and remediation	0.2	0.2
Construction	2.6	2.1
Wholesale and Retail Trade	12.0	5.7
Transport and Storage	3.0	2.9
Accommodation and Food Service	1.7	0.9
Information and Communication	23.4	33.5
Financial and Insurance activities	9.1	11.4
Real Estate Management	0.2	0.0
Professional, Scientific & Technical	3.9	3.6
Administration and Support Service Activities	2.9	3.2
Public Administration and Defence	3.9	5.2
Education	12.3	6.4
Human Health and Social Work activities	7.0	6.1
Arts, Entertainment and Recreation	0.3	0.2
Other Service Activities	0.9	0.1
Activities of Household as employers	1.1	0.0

Source: Computed from the unit records of Periodic Labour Force Survey 2023-24 (Employed Graduates and Postgraduates, 22 ≤ Age ≤ 27, 2023-24)

Appendix 3

Identifying Green Economic Activity

Green Economic Activity	*Industrial National 2008 Classification*
Repair	
Repair of Fabricated Metal Products	33119 to 33111
Repair of Machinery	33129 to 33121
Repair of Electronic and Optical Equipment	33133 to 33131
Repair of Electrical Equipment	33140
Repair of transport equipment, except motor vehicles	33150
Repair of Other Equipment	33190
Waste Management	
Collection of Non-Hazardous Waste	38110
Collection of Hazardous Waste	38120
Treatment and Disposal of Non-Hazardous waste	38210
Treatment and Disposal of Hazardous waste	38222 to 38221
Remediation activities and other waste management	39000
Sewerage and Treatment	37003 to 37001
Material Recovery	
Material Recovery	38300
Retail Sales of Second-hand Goods	
Retail Sale of Second-hand Goods	47740
Renewable Energy	
Renewable Energy	35106 and ,35105 ,35101
Sustainable Farming	
Organic Farming	01122 to 01121
Mixed Farming	1500
Growing of plants for planting	1301
Seed Processing for Propagation	1640

Source: National Industrial Classification 2008

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