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Towards the 2025 System of National Accounts: Well-being and sustainability

Measuring the Contribution of Labour Composition in Gross Value Added in India – The Human Capital Approach

Prepared by the Reserve Bank of India[1]

Summary

Key policy debate on growth and sustainability occurs at the intersection of the production process and the labour market. Hence, integrating labour market statistics with National Accounts Statistics (NAS) would be instrumental in understanding crucial policy questions on inclusive growth, distribution, and productivity issues. With this background, the paper presents the RBI India KLEMS framework that constructs labour accounts consistent with NAS and examines the role of labour and its composition on the trajectory of GVA growth in India. The paper's findings indicate a structural change in employment from agriculture to construction and services and increased workforce regularization in the manufacturing sector. The workforce distribution across education categories shows a general increase in education levels for all workers, especially in India's capital-intensive manufacturing and services sectors. The growth accounting decomposition shows that employment contributed around 25 percentage points to output growth, with labour quality contributing an additional five percentage points to output growth on average from 1980-81 to 2021-22.

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I. Introduction

2. Gross Value Added (GVA), derived from the System of National Accounts (SNA), has emerged as the primary metric for assessing a nation's economic performance. However, over the years, researchers and policymakers have made steady efforts to measure people's well-being instead of economic growth. In India, GVA data is compiled by National Accounts Statistics (NAS). The labour market data, on the other hand, is based on household-level surveys conducted by National Sample Survey Office (NSSO) and Periodic Labour Force Survey (PLFS). The NAS does not provide a detailed articulation of labour accounts, and hence, integrating labour market statistics with NAS would be instrumental in understanding crucial policy questions on issues of inclusive growth, distribution, and productivity. With this background, the paper presents the RBI India KLEMS framework that constructs labour accounts consistent with NAS and examines the role of labour and its composition on the trajectory of GVA growth in India. The KLEMS[2] framework is based on growth accounting identity that relates the aggregate growth of GVA to labour and capital used in the production process and the Solow's residual.

3. Measuring labour composition (or labour quality) is essential for several reasons. First, labour and capital are necessary factor inputs used in the production process, but unlike capital, labour is not represented in the System of National Accounts. Second, as the frontier of skills is evolving rapidly, India is witnessing a remarkable shift from informal employment to formal and regular employment in the last decade. The labour input unadjusted for quality does not reflect the skill dimension. Conventional measures of labour productivity growth measure output per unit of employment by solely looking at labour as a homogenous unit. "As a result, an hour worked by a highly experienced surgeon and an hour worked by a newly hired teenager at a fast-food restaurant are treated as equal amounts of labour- OECD (2001)." Hence, it is essential to measure the labour index to assess the impact of labour quality and the contribution of labour input to output growth. Further measuring the labour composition index can be a starting point for measuring the effect of intangible investment and building up the human capital index, which is an important measure of welfare and sustainability.

4. The objective of this paper is to present the long-term time series of labour input using the KLEMS growth and productivity framework[3]– an implicit indicator of human capital for the working population of India. The labour input has two components: employment and labour quality index. Employment measures the number of persons employed by sectors of the economy, whereas the labour quality index depicts the contribution of knowledge and skills that empower the working population to drive economic growth and productivity. The labour quality index explicitly accounts for the heterogeneity of workforce by assigning weights to different workers based on their wage shares which are associated with educational qualification and industry type. By including labour quality in labour input estimation, a shift in the share of low skilled to high skilled workers reflects an increase in labour or productivity higher than the growth of number of persons employed.

5. There are various measurement challenges in designing the labour accounts for India in alignment with the NAS framework. First, NAS data are published annually, while labour force surveys in India prior to 2017-18 were conducted with a gap of 5 years. Furthermore, the earnings data for the self-employed workers are not available separately in the NAS and are included in mixed-income. To fill this gap, an attempt has been made in the RBI KLEMS database to construct the annual time series of labour accounts consistent with the NAS classification of industries. The labour input accounts are computed for aggregate and subsectors of the economy. The sectors are categorised as aligning with the National Accounting System of India. The time period of the study is 1980-81 to 2021-22. Following the growth accounting framework, this paper analyses the contribution of labour input and its composition (labour quality) in the gross value added (GVA) growth.

[2] KLEMS stands for analysis of Capital (K), Labour (L), Energy (E), Material (M) and Service (S) input in explaining output and productivity growth.

[3] Refer to RBI KLEMS Manual (2024) for details https://www.rbi.org.in/scripts/klems.aspx

6. The findings of the paper present a notable shift in the nature and quality of employment from the agriculture sector to the construction and services sectors and an increased regularization of the workforce in the manufacturing sector. For the total economy, labour quality growth increased by 0.7 per cent per annum from 1980-81 to 2021-22. An analysis of the workforce distribution across education categories shows a general increase in education levels for all workers, especially those employed in capital-intensive manufacturing and services sectors. The labour quality indicator is higher in capital-intensive manufacturing and service sectors, while construction and agriculture sectors exhibit lower growth in labour quality indices, attributed to the prevalence of low-skilled workers. The growth accounting exercise shows that employment contributed to around 25 percentage points to output growth, with labour quality contributing an additional five percentage points to output growth on an average from 1980-81 to 2021-22.

7. The rest of the paper is arranged as follows. Section 2 describes the methodology and data sources used to construct the labour input index in India. Section 3 presents some stylised facts on labour quality in India during 1980-81 to 2021-22. Section 4 presents the findings on the contribution of labour input and its composition to output growth for aggregate and disaggregated sectors. The final section concludes and highlights some outstanding issues in integrating KLEMS's labour accounts with the NAS framework.

II. Methodology and Dataset

8. The source of human capital could be through investment in education, work experience, training and skill development. Following Jorgenson et al. (1987) and the EU KLEMS Manual, the RBI KLEMS framework has designed a labour input index that estimates employment growth adjusted for quality. This framework distinguishes workers according to their educational attainment and experience and weights each category's growth rate using their marginal productivities. The labour input index is given as a trans-log index of its individual components where weights are the two-period average share of the components in the value of labour compensation. The growth of the labour input index is given as

$$\Delta\, ln\, L = \sum \bar{v} \Delta\, ln\, H\text{ijt} \qquad (1)$$

where L is the aggregate labour index, Hijt indicates the total persons worked by a particular education type 'i' in industry 'j' in period t. i=1,2…n and denotes the number of education categories. j=1,2,….n and denotes the number of industries. $\sum$ denotes summation over all education categories.

$\bar{v}$ is the average share of each type of employment in the value of labour compensation.

$\bar{v} = ½\, [vi_t + vi_{t-1}]$ and $vi = wi \quad Hi/\sum wi \quad Hi$

Here, vi is the value share of labour for the ITH education category. wi is the wage rate of labour for the ith education category.

9. Following the theory in growth accounting models, it is assumed that marginal revenue equals marginal costs. Thus, the weighting procedure ensures that labourers who get a higher wage will have a higher influence on the input index. Thus, the growth in the labour input index incorporates both labour quantity and quality growth.

10. It follows from equation (1) that the growth in the labour quality index can be expressed as

$$\Delta\, ln\, \text{Ql} = \sum \bar{v} \Delta\, ln\, H\text{ijt} - - \Delta\, \text{ln} \sum Hj{,}t \qquad (2)$$

where Ql is the quality index of labour, Hjt is the number of labours unadjusted for educational characteristics. In equation (2), the change in labour input is indicated by the first term on the right-hand side, while the change in the total number of employees in industry 'j' is indicated by the second term. The difference between the two is the aggregate labour quality index, which tracks the shifts in the educational attainment of the country's labour force.

11. Once the employment and labour composition (or labour quality) index is constructed, following the growth accounting framework by Jorgenson, Gollop and Fraumeni (1987) and Jorgenson et al. (2005), the relative contribution of employment and labour quality to output growth is estimated. Under the assumption of perfect competition and constant returns to scale, the output growth of an industry is computed as a weighted share of factor input growth and TFP growth. Compensation of factor inputs are used as weights. The output growth accounting decomposition is represented by the following equation:

$$\Delta lnY_t = \bar{v}_K \Delta lnK_t + \bar{v}_L \Delta lnL_t + \bar{v}_L \Delta lnLQ_t + TFP_t \qquad (3)$$

where ΔlnY_t is the growth in real output growth for the total economy. ΔlnK_t and ΔlnL_t are growth in factor inputs- capital (K) and labour (L). $\Delta lnLQ_t$ denotes growth in labour quality.$\bar{v}$ is two-period average compensation shares in gross value added. TFP_t is the Total factor of productivity growth. All variables are indexed over time t. By implementing equation (3), we can compute the proportion of output growth that is accounted for growth in employment, labour quality, capital and TFP growth, respectively.

12. For computing the labour quality index, the data required is the number of persons employed and earnings (labour compensation) by educational qualifications of the workers across different industries. It is important to note that there are several challenges in constructing the time series of employment and earnings data for India. For instance, the back series of employment data is based on quinquennial survey rounds of NSSO, which were published with a gap of five years from 1980 to 2011, and only from 2017 onwards did the PLFS publish the annual employment series. Further, there is a large informal labour market in India, and the information on the earnings of different categories of workers, especially self-employed workers, is not consistently available in NAS and labour force survey rounds. To fill this gap, the following treatments are done:

13. For employment time series, worker participation rates are obtained from the unit-level Employment-Unemployment Survey (EUS) rounds published by NSSO (32nd to 68th round.[4]) and Periodic Labour Force Survey (PLFS) (2017-18, 2018-19, 2019-20, 2020-21, 2021-22). As different labour force survey rounds use different industry classifications (NICs), a concordance has been worked out among NIC 1970, NIC 1987, NIC 1998, and NIC 2007 industries classifications. The worker participation rates are then applied to the corresponding period's population estimates from the census to estimate the number of persons employed. The employment estimates for the intervening years between the major employment survey rounds have been obtained by linear interpolation. The interpolation has been centred around 1st October to align with the national income estimates' mid-year, which is the Indian fiscal year that runs from April to March. The PLFS, which has a different time coverage, runs from July to June of the following year, with January 1st serving as its centre. As a result, two phases are involved in our employment estimation for financial years. First, we estimated employment for several years using the population estimate as of January 1st. Next, the employment projection for the financial year—as of October 1st—is obtained by applying interpolation.

14. When the times series of employment is obtained, the next step is to account for the heterogeneity of worker groups. Skills are measured in terms of educational characteristics. The labour quality growth rates have been computed using five education categories, namely: (i) below primary (– Standard I to IV), (ii) primary (Standard V), (iii) middle (standard VIII), (iv) secondary & higher secondary (Highschool/ Standard X and Intermediate/ Standard XII), and (v) above higher secondary (Graduation and above)[5].

[4] The major quinquennial rounds are 32nd (1977-78), 38th (1983), 43rd (1987-88), 50th (1993-94), 55th (1999-00), 61st (2004-05), 68th (2011-12).

[5] The education categories in NSSO and PLFS, as well as household survey rounds, are defined as follows: Persons who are literate through formal schooling and are yet to pass primary standard education are defined as below primary. Persons who have passed standard V are categorised as primary, those who have passed standard VIII as middle, persons who have completed Standard X and XII are secondary and higher secondary and persons who have completed graduation and above are categorised as higher secondary.

15. The wages of different types of workers based on education levels are obtained from household employment survey rounds. While the earnings of casual and regular wage workers are estimated directly from the NSSO and PLFS survey rounds, the earnings of self-employed workers are estimated econometrically due to the unavailability of data. For estimating the earnings of self-employed persons following the standard practise in the EU KLEMS database, a Mincer wage equation is used after correcting for sample selection bias using Heckman's two-step procedure (Heckman, 1976).[6] The Mincer function has been applied to the earnings of casual and regular workers, and the results are used to find the corresponding earnings of self-employed workers. The earnings have been regressed on dummy variables representing gender, age groups, urban or rural location, industry of occupation, education level, marital status and social exclusion. The first stage identification factors are age, gender, marital status, and type of household. The corresponding earnings of the self-employed are obtained as the predicted value with similar traits. Then, the average wage per day is computed for different types of employment. Finally, when wages are obtained as per educational distribution, then the computation of the labour quality index is done following equations (1) and (2) stated above.

III. Stylised facts on Employment Quality

16. Over the years, there has been a perceptible shift in the employment structure in India. The agriculture sector, however, continues to be the largest employment generator, though the share of employment in agriculture reduced from 68.5 per cent in 1983-84 to 42.8 per cent in 2021-22. The workforce that transitioned away from agriculture found opportunities predominantly in the construction and services sectors. The proportion of employment in construction increased from 2.3 per cent in 1983-84 to 12.3 per cent in 2021-22, while the share of employment in services sector increased from 17.7 per cent to 33.5 per cent during the same period. This shift indicates a structural transformation in employment, with workers moving from agriculture to construction and services, while the share of manufacturing employment remained unchanged (Figure 1).

Figure 1

Structure Change in Employment, in per cent

Source: Authors calculations based on RBI KLEMS 2024

17. Although the structural shift in employment has occurred from the agriculture sector to the construction and services sectors, it is important to analyse the quality of employment in these sectors. The selected attributes used to examine employment quality are a) the nature of employment-organised/unorganised, b) the education profile of workers, and c) compensation paid to workers. Nature of employment has been a widely used as a proxy for measuring job quality in developing nations. The labour market in India has three types of

[6] The Heckman model is expressed in terms of two equations: a selection equation to explain whether or not to participate in labour market. The Heckman model is usually a probit estimation, which takes the value one if the person is working, 0 otherwise.

workers - Regular, Casual and Self-employed. Regular employment is considered more stable and of better quality than casual and self-employment as most regular workers have written job contracts (Nayyar, 2012; Dewan and Peek 2007, Papola and Sharma 2015). Workers' educational qualifications are considered indicators of job quality, as workers with higher education secure better quality jobs in terms of job security, benefits, and higher wages (Aggarwal & Goldar, 2019). Compensation paid to workers indicates job quality as it is a primary source of material well-being (Jackson and Kumar, 1998). Compensation paid to workers captures individual income and gives an idea of whether labour income can support the minimum standard of living.

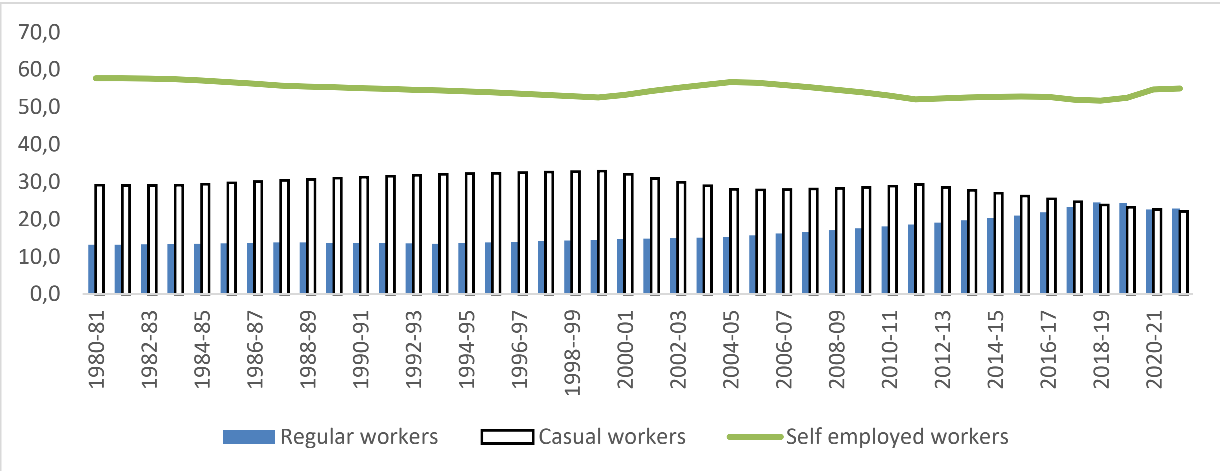
A. Nature of Employment: Formal/Informal

18. The first aspect of job quality relates to the nature of employment. The labour force survey data shows that most of the workforce is engaged in the informal/unorganised sector in India. However, the share of unorganised/informal workforce in the economy has been declining over time. Figure 1 and 2 provides the composition of employment in terms of regular (formal employment), self-employed and casual workers (informal employment). The share of self-employed and casual workers in the total workforce accounted for 77 per cent in 2021-22 compared to 86.8 per cent in the 1980s. The share of regular workers with job contracts increased from 13.2 per cent in 1980-81 to 22.9 per cent in 2021-22 (figure 2). The pattern observed on greater regularisation of workforce came from manufacturing and services sectors. In manufacturing, the share of regular workers increased significantly from 27.6 per cent in 1980-81 to 49.9 per cent in 2021-22. In the services sector, the share of regular workers increased from 44.8 per cent in 1980-81 to 48.1 per cent in 2021-22.

19. On the other hand, the agriculture and construction sectors have a high share of informal workers. Of the total informal workforce in the agriculture sector, the share of self-employed workers increased from 63.6 per cent in 1980-81 to 78.2 per cent in 2021-22. The construction sector, which has become one of the fastest-growing sectors in terms of employment generation, has mostly casual employees with no written job contracts. The share of casual workforce in the construction sector was 71.2 per cent in 1980-81, which increased to 82.3 per cent in 2021-22 (figure 3).

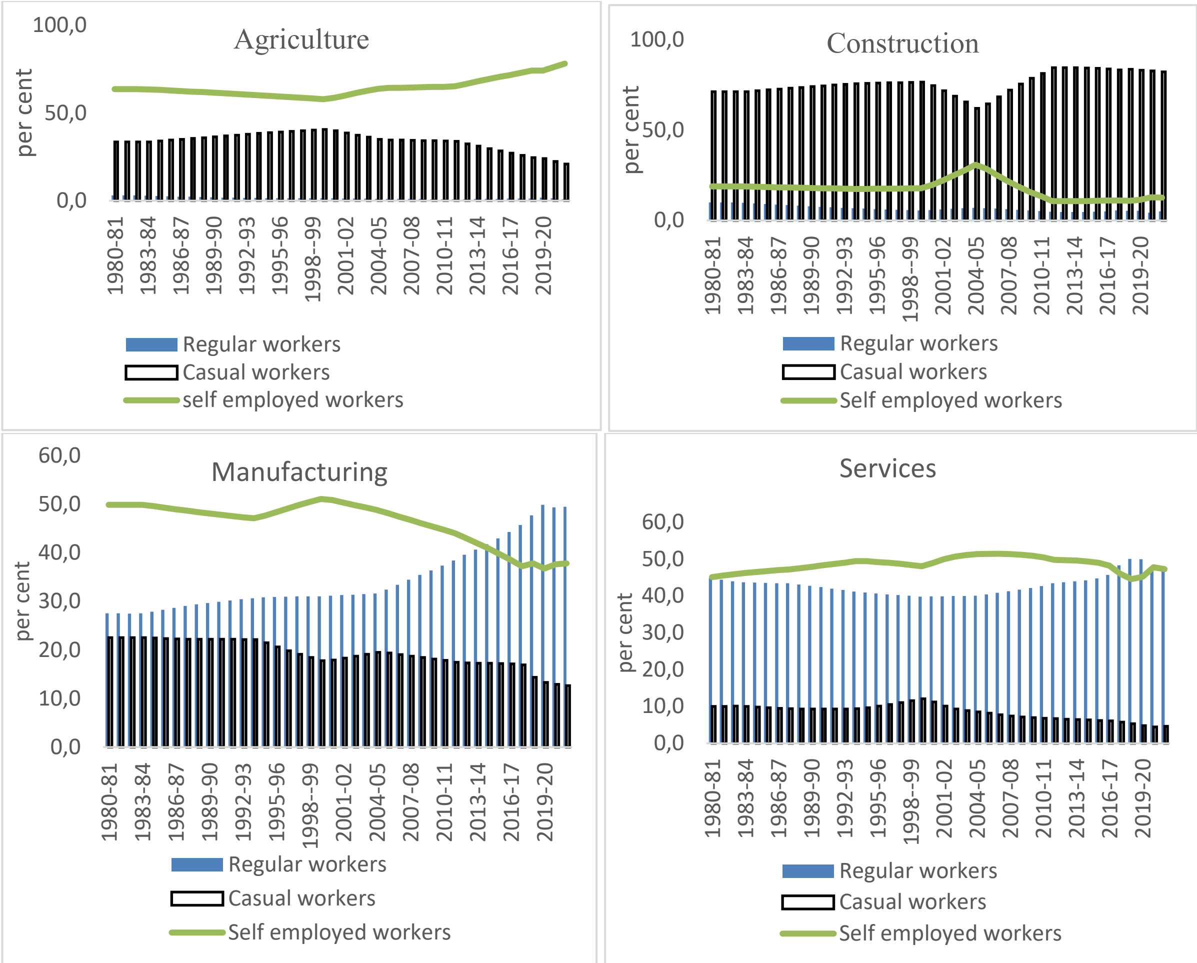
Figure 2

Composition of workers for the total economy, in per cent



Source: Authors calculations based on RBI KLEMS 2024

Figure 3
Composition of workers in broad sectors, in per cent



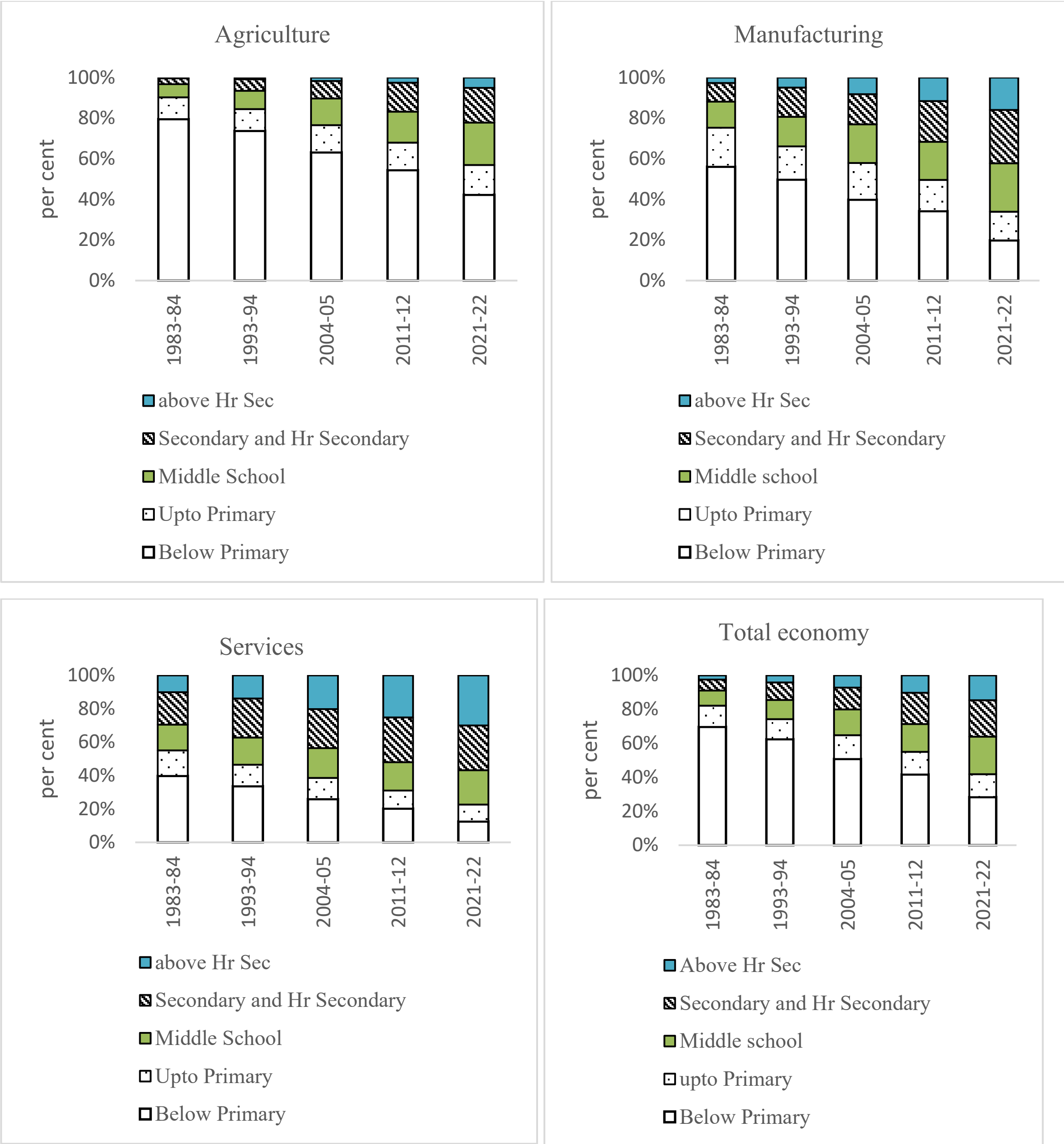
Source: Authors calculations based on RBI KLEMS 2024

B. Education Attainment of Workers

20. The second aspect of job quality relates to the educational attainment of workers. When we analyse the distribution of the workforce by broad education categories from 1983-84 till 2021-22, it is observed that the general level of education for all workers has increased. This is indicated by a decrease in the proportion of workers with below primary education and an increase in the proportion of workers with above higher secondary or tertiary education. Among disaggregated sectors, the skill intensity of sectors is quite different. The agriculture sector has the highest number of workforce with primary education level. There has been a significant increase in the number of workers with middle, secondary and higher secondary degrees in the manufacturing sector.

21. On the other hand, the services sector has the largest share of tertiary-educated workers. The proportion of employed in services sector with above higher secondary education was around 10 per cent in 1983-84 which increased to 30 per cent in 2021-22. This implies jobs available in the services sector are increasingly becoming high-skill intensive in nature, whereas job requirements in the manufacturing sector remain medium skill intensive (figure 4)

Figure 4
Educational distribution of workforce, in per cent



Source: Authors calculations based on RBI KLEMS 2024

C. Labour Income Share

22. The third aspect of job quality relates to the workers' compensation. In 1981-82, the labour income shares in GVA varied from 80 per cent in construction to 38 per cent in manufacturing (Table 1). However, due to structural change and increasing capital intensity across sectors, a downward trend in labour income share is observed for the total economy and across all subsectors. The labour income share declined by 2.2 percentage points for the total economy,1.4 percentage points for agriculture, 12.7 percentage points for mining and quarrying,6.4 percentage points for manufacturing, 2.7 percentage points for construction and 2.6 percentage points for services sectors (Table1). Across sectors, real wages grew consistently, except for construction. The International Labour Organisation (ILO) (2014) finds that across developed and emerging nations, if the growth rate of real wages is slower

than labour productivity growth, then the labour income share declines.[7] Examining wage productivity data for India, it is observed that real wage growth lagged behind labour productivity growth for the total economy and subsectors for India, with the divergence being the sharpest in the manufacturing sector (Table 2). The finding also matches Goldar and Das 2020, where, along with wage productivity mismatch, they find that an increase in capital intensity appears to be an important factor in explaining the declining trend of labour income share in India.

Table 1
Labour income share in per cent

Sectors	*1981-82*	*1991-92*	*2001-02*	*2021-22*
Total economy	54.1	53.6	50.8	51.9
Agriculture	57.5	56.2	55.2	56.1
Mining and Quarrying	37.3	32.1	34.2	24.6
Manufacturing	37.9	33.9	32.0	31.5
Construction	80.0	80.3	77.9	77.3
Services	57.0	58.6	53.2	54.4

Source: Authors calculations based on RBI KLEMS 2024

Table 2
Growth in real wages and labour productivity in per cent per annum

Sectors	*Growth in Labour Productivity*	*Growth in Real wages*
Total economy	4.42	4.3
Agriculture	3.11	3.00
Mining and Quarrying	3.95	2.4
Manufacturing	5.14	4.5
Construction	-0.24	-0.2
Services	3.84	3.7

Source: Authors computed from KLEMS data 2024, and wage data compiled from Goldar and Das 2020

23. Next, we combine the three attributes of job quality for disaggregated sectors and identify sectors with a relatively high proportion of skilled workers, pay higher wages, and employ fewer casual workers. These sectors, hence, provide relatively better quality jobs. It is observed that the agriculture sector employs low-skilled workers (skill measured in terms of educational attainment) with a high proportion of casual and self-employed workers and provides relatively lower wages. The construction sector also employs low-skilled workers and has a high share of casual workers with relatively higher wages. Thus, the construction sector is a natural choice for low-skilled workers to relocate from the agriculture sector. In the manufacturing sector, capital-intensive industries like chemicals, machinery and equipment and pulp and paper products employ workers with high levels of education and provide relatively higher average wages. Within the services sector, business and financial services, health, education, public administration and defence sub-sectors have a high quality of employment, measured in terms of the level of education, the proportion of casual workers and average wage per day (Table 3).

[7] Labour income share = (w/l)/(p.v) (1)
= (w/p)/ (v/l) (2)
= real wage/labour productivity (3)
where v is gross value added, l=employment, w=nominal wage rate, p=output price

Table 3
Level of Higher education, proportion of casual workers and average wage per day in 2021-22

Disaggregated Sectors	*Level of Higher education of workers (above higher secondary education)*	*Proportion of casual workers*	*Average wage per day*
Agriculture, Hunting, Forestry and Fishing	Low	High	Low
Mining and Quarrying	Low	High	High
Food Products, Beverages and Tobacco	Low	Low	Low
Textiles, Textile Products, Leather and Footwear	Low	Low	Low
Wood and Products of wood	Low	Low	Low
Pulp, Paper, Paper products, Printing and Publishing	High	Low	High
Coke, Refined Petroleum Products and Nuclear fuel	High	Low	Low
Chemicals and Chemical Products	High	Low	High
Rubber and Plastic Products	High	Low	Low
Other Non-Metallic Mineral Products	Low	High	Low
Basic Metals and Fabricated Metal Products	High	Low	Low
Machinery, nec.	High	Low	High
Electrical and Optical Equipment	High	Low	Low
Transport Equipment	High	Low	Low
Manufacturing, nec; recycling	Low	Low	Low
Electricity, Gas and Water Supply	High	Low	High
Construction	Low	High	High
Trade	Low	Low	Low
Hotels and Restaurants	Low	Low	Low
Transport and Storage	Low	Low	High
Post and Telecommunication	High	Low	High
Financial Services	High	Low	High
Business Service	High	Low	High
Public Administration and Defense	High	Low	High
Education	High	Low	High
Health and Social Work	High	Low	High
Other services	Low	Low	Low

Note: Sectors are classified as high when the level of education, the proportion of casual workers and the wage rate are above the total economy average. Similarly, sectors are classified as low if the level of higher education is high, the proportion of casual workers is low, and the average wage is below the national average.
Source: Authors computation from KLEMS data 2024

IV. Labour Quality Growth and its Contribution to GVA Growth

24. In this section, we present the estimates of labour input index (employment and quality) computed using KLEMS framework as described earlier in section 2 of the paper. We also account for the contribution of labour and its composition (labour quality) to GVA growth for 1980-81 to 2021-22.

A. Growth in employment

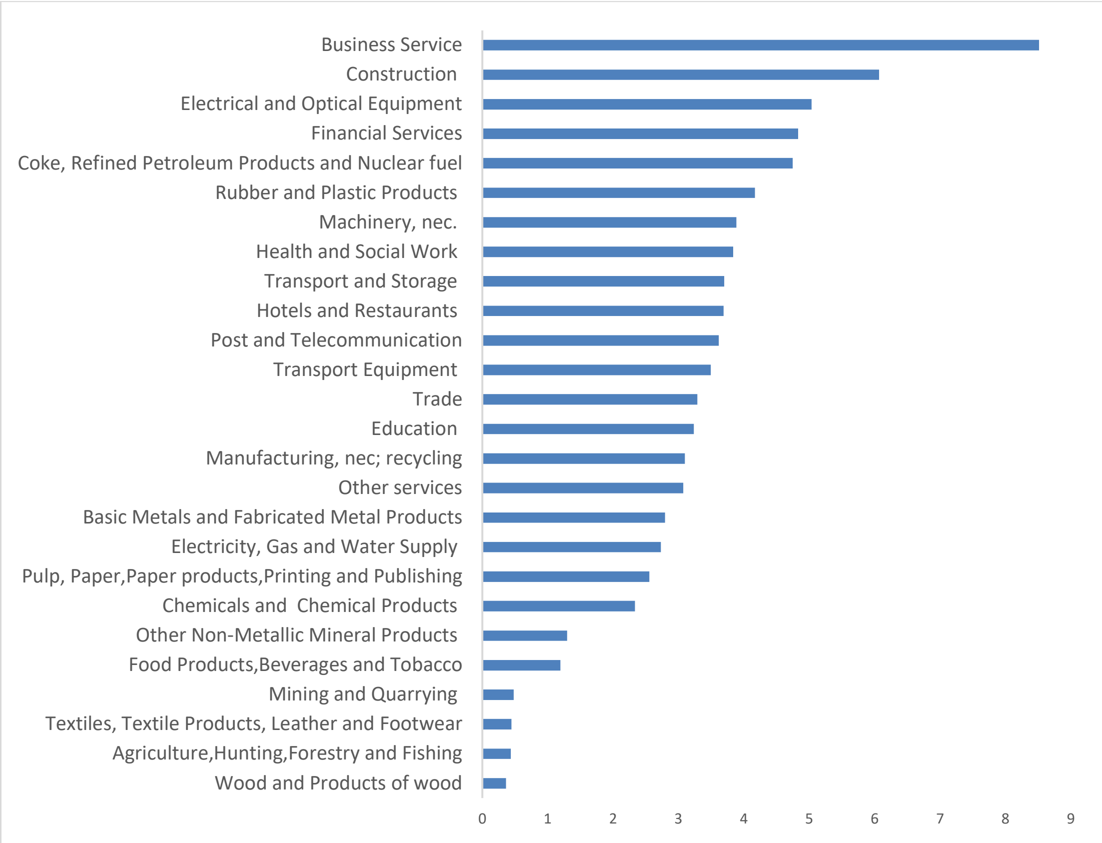
25. It is observed that employment growth for the total economy was 2.7 per cent per annum during 1980-81 to 2021-22, mostly driven by the construction and services sectors. Within the services sectors, the fastest growing sectors in employment generation were business services, construction, electrical and optical equipment and financial services subsectors. All services subsectors recorded employment growth above 3 per cent per annum. A subperiod analysis shows employment growth slowed down from 2000-01 to 2021-22 compared to 1980-81 to 1999-00. The slowdown in employment growth is mainly emitted from the agriculture and mining sectors. As per Krishna et al. (2016), the deceleration in employment growth in the agriculture sector was on account of lower labour productivity due to the use of old technology and lack of investment in the agriculture sector. The construction sector, on the other hand, witnessed a high growth in employment in both subperiods, indicating the low-skilled workers of the agriculture sector were primarily absorbed in the construction sector as casual workers (table 4).

Table 4
Growth in employment by Broad sectors, in per cent per annum

Subsectors	*1980-81 to 1999-00*	*2000-01 - 2021-22*	*1980-81 to 2021-22*
Total economy	2.8	2.5	2.7
Agriculture	1.0	-0.1	0.4
Manufacturing	2.6	2.0	2.3
Construction	5.9	6.2	6.1
Mining and Quarrying	2.8	-1.8	0.5
Electricity, Gas and Water Supply	1.8	3.6	2.7
Services	3.5	2.9	3.2

Source: Authors computation from KLEMS data 2024

Figure 5
Growth in Employment by disaggregated sectors 1980-81 to 2021-22 per cent per annum



Source: Authors computation from KLEMS data 2024

B. Growth in the Labour Quality Index

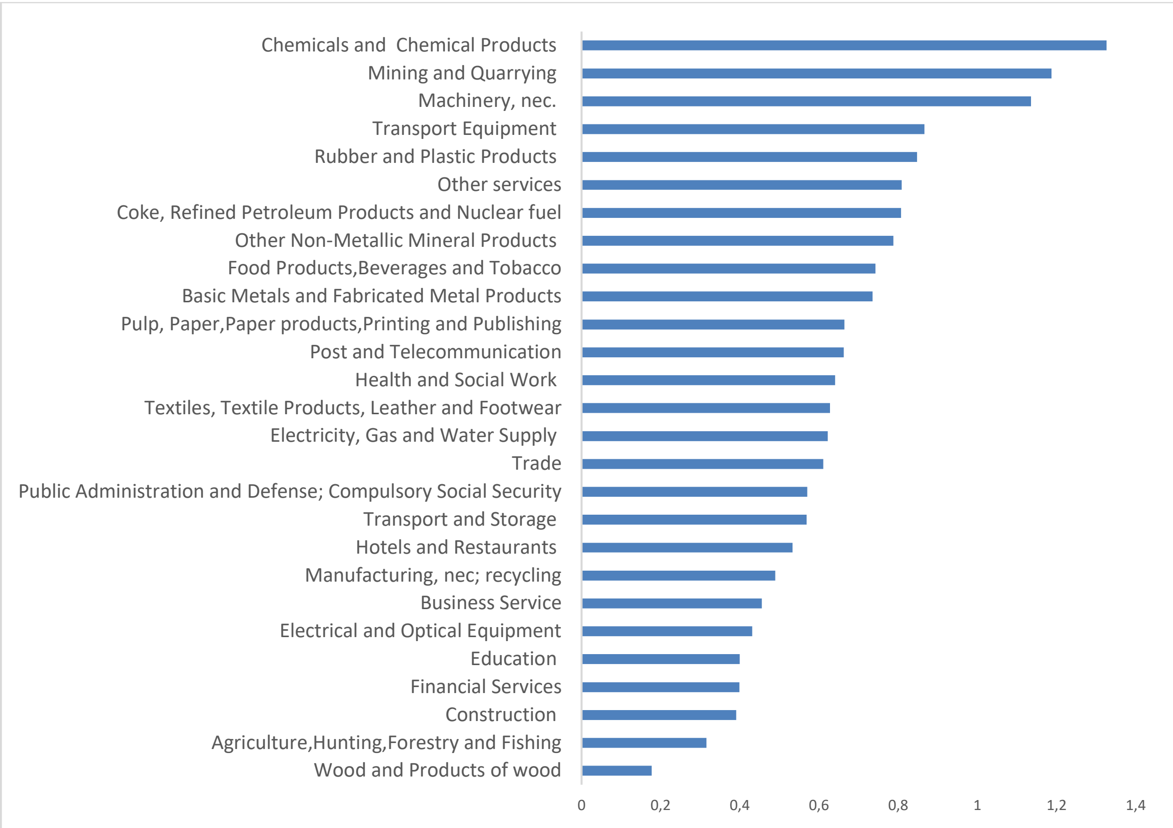
26. We next examine the growth in the labour composition index, which measures the change in the skill of the workers over the period and their reward for the skill in terms of earnings. Thus, the index is sensitive to the measure of earnings data. For the total economy, the labour quality index has increased on an average by 0.7 per cent per annum from 1980-81 to 2021-22. The growth of the labour quality index has been relatively low for agriculture and construction and was high for the manufacturing, mining, quarrying and services sectors. A subperiod analysis shows that the labour quality index improved for agriculture, mining, quarrying and services sectors from 2000-01 to 2021-22. However, the quality index's growth decelerated for manufacturing, construction and electricity, gas and water supply subsectors. At the disaggregated industry level, growth in labour quality has been fastest in capital-intensive manufacturing sectors such as chemicals, machinery, and transport equipment. Among the services sector, subsectors like health, social work and telecommunication recorded the fastest growth in the labour quality index (figure 6). Subsectors like business, education and financial services have a slower growth in the quality index as these sectors already have a very high share of skilled workers (Krishna et al., 2016).

Table 5
Growth in Labour Quality by broad sectors, in per cent

Sectors	*1980-81 to 1999-00*	*2000-01 - 2021-22*	*1980-81 to 2021-22*
Total economy	0.72	0.60	0.66
Agriculture	0.28	0.34	0.32
Manufacturing	0.87	0.63	0.74
Construction	0.46	0.33	0.39
Mining and Quarrying	0.74	1.58	1.19
Electricity, Gas and Water Supply	0.83	0.44	0.62
Services	0.55	0.59	0.56

Source: Authors computation from KLEMS data 2024

Figure 6
Growth in labour quality, disaggregated sectors 1980-81 to 2021-22 per cent per annum

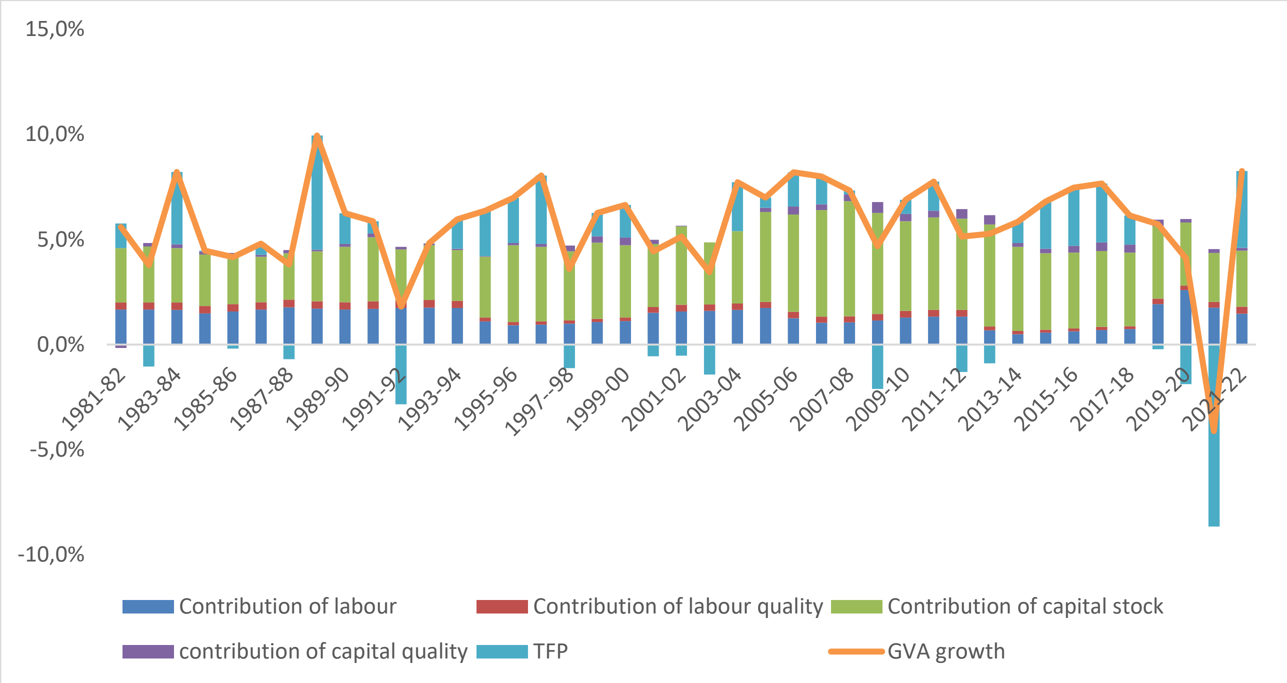


Source: Authors computation from KLEMS data 2024

C. Contribution of Labour Input to Output Growth

27. The growth accounting decomposition from 1980-81 to 2021-22 shows that the labour quality index contributed to around five percentage points to output growth on average. Employment contributed to around one-fourth of output growth during the same period. The contribution of labour was relatively high during the 1980s, and since the mid-1990s, capital emerged as the dominant input and the leading contributor to growth. The labour input (combined employment and quality) accounted for 30 per cent of output growth during the study period (figure 7).

Figure 7
Sources of GVA growth, Total Economy in per cent

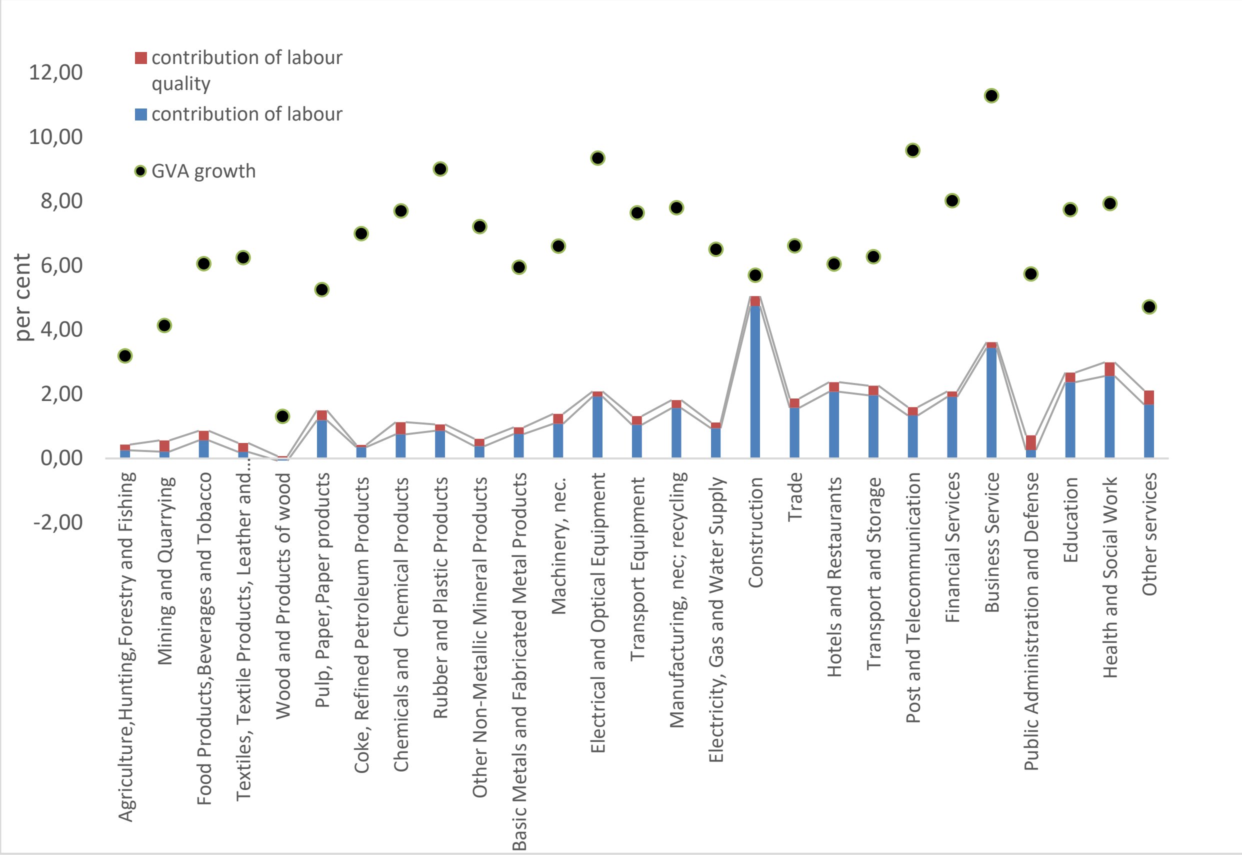


Source: Authors computation from KLEMS data 2024

28. A disaggregated analysis of growth contribution within the manufacturing sector reveals that the contribution of labour quality to output growth was high for textiles, pulp, paper products, printing and publishing, machinery and equipment. Within the services sector, the labour quality growth contributed more than eight percentage points to output growth for public administration and defence subsectors. Other service subsectors where labour quality contributed more than five percentage points to output growth include health and social work, transport and storage and hotel and restaurants. Besides, mining, quarrying, and construction sectors also have more than 5 per cent of output being driven by labour quality growth(Figure 8).

Figure 8

Average contribution of labour and labour quality to output growth, disaggregated sectors, 1980-81 to 2020-21



Source: Authors computation from KLEMS data 2024

V. Conclusion

29. The study employing the KLEMS methodological framework has presented important findings using labour market data from diverse sources. First, there has been a notable shift in employment from agriculture to the construction and services sectors, accompanied by increased workforce regularisation in the manufacturing sector. The employment growth was fastest in business services, construction, electrical and optical equipment, and financial services from 1980-81 to 2021-22.

30. Second, an analysis of the workforce distribution across educational categories shows a general increase in education levels for all workers. Capital-intensive industries like chemicals and machinery exhibit higher education levels, fewer casual workers, and higher average wages. Within the services sectors, business and financial services, health, education, public administration, and defence subsectors display high-quality employment. However, the wage productivity data for India indicates a lag in real wage growth behind labour productivity growth, particularly in the manufacturing sectors. The labour quality index computed based on educational characteristics of the workforce shows that the growth in labour quality increased on an average by 0.7 per cent per annum from 1980-81 to 2021-22. At the disaggregated industry level, growth in labour quality has been fastest in capital-intensive manufacturing sectors such as chemicals, machinery, and transport equipment. Among the Services sector, subsectors like health and social work, other services, and telecommunication recorded the fastest growth in the labour quality index. Subsectors like business services, education and financial services recorded slower growth in the quality index mainly on account of the high base effect due to the prevalence of a high share of skilled workers.

31. Third, the growth accounting exercise shows that the employment contributed to around 25 percentage points to output growth, with labor quality contributing an additional five percentage points to output growth on average during 1980-81 to 2021-22. Thus, the labour input (combined employment and quality) accounted for 30 per cent of overall output growth during 1980-81 to 2021-22. In the manufacturing sector, labour quality contributed significantly to output growth in textiles, pulp, paper products, printing and publishing, and machinery. In Services, subsectors like public administration, defense, health, social work, transport and storage, and hotels and restaurants witnessed substantial contributions from labour quality to output growth. However, employment and labour quality played a more significant role in driving output growth in the 1980s, while capital emerged as the dominant input since the mid-1990s.

32. Going forward, the labour data for India derived from KLEMS framework can be integrated with NAS data as the KLEMS framework maintains consistency with NAS. A number of countries like the Netherlands, Denmark, Norway, Switzerland, Australia, Malaysia, and Iran have already published labour accounts in their System of National Accounts. The report on guidance for enhancing and broadening the SNA framework (2023) mentions that the labour accounts in SNA should have four quadrant tables covering information on jobs, number of persons employed (including regular, casual and self-employed workers), volume (that is hours worked) and payments. For India, there are some limitations to constructing the accounts of jobs and payments. The labour force survey rounds are household-based surveys from which we can estimate the number of persons employed and employment volume.

33. Further, based on KLEMS framework labour can also have an indicator on labour quality which shows labour composition effect measured on basis of skills of workers. Efforts should be made to publish the statistics on job and vacancy posting from establishment-based or enterprise-level surveys. Recently, the Quarterly Report on Employment Scenario published by the Labour Bureau started publishing enterprise-wise vacancy details from 2021 onwards. Information can also be derived from private surveys, though the industry-level information is limited in nature. Thus, there is a need to fill the data gaps for building the long time series in jobs and job vacancies consistently. Another data challenge is estimating the wages of self-employed persons, which accounts for the majority of employed individuals in India. For overcoming the unobserved wages for self-employed persons in NSSO survey rounds, a mincer equation is used in the KLEMS framework. The payment quadrant is available in NAS, where payment of self-employed persons are clubbed under mixed income. The mixed-income contains a surplus accrued from the production and labour income of self-employed persons. Hence, integration with KLEMS accounts would facilitate the segregation of mixed-income between earnings of capital and earnings data for self-employed, regular and casual workers in NAS.

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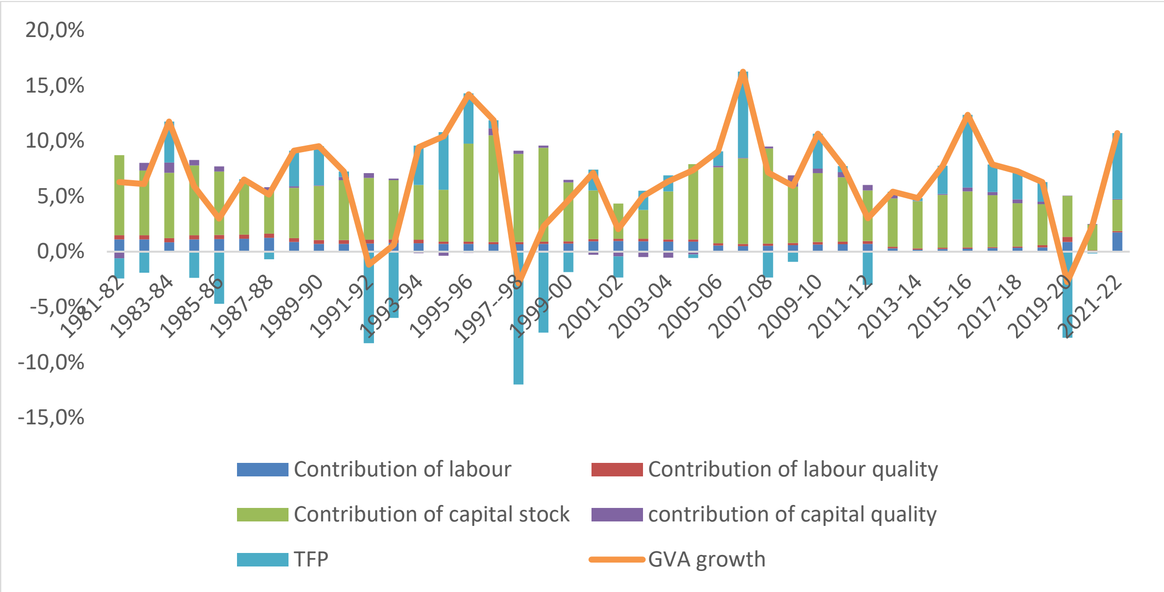
Annex I

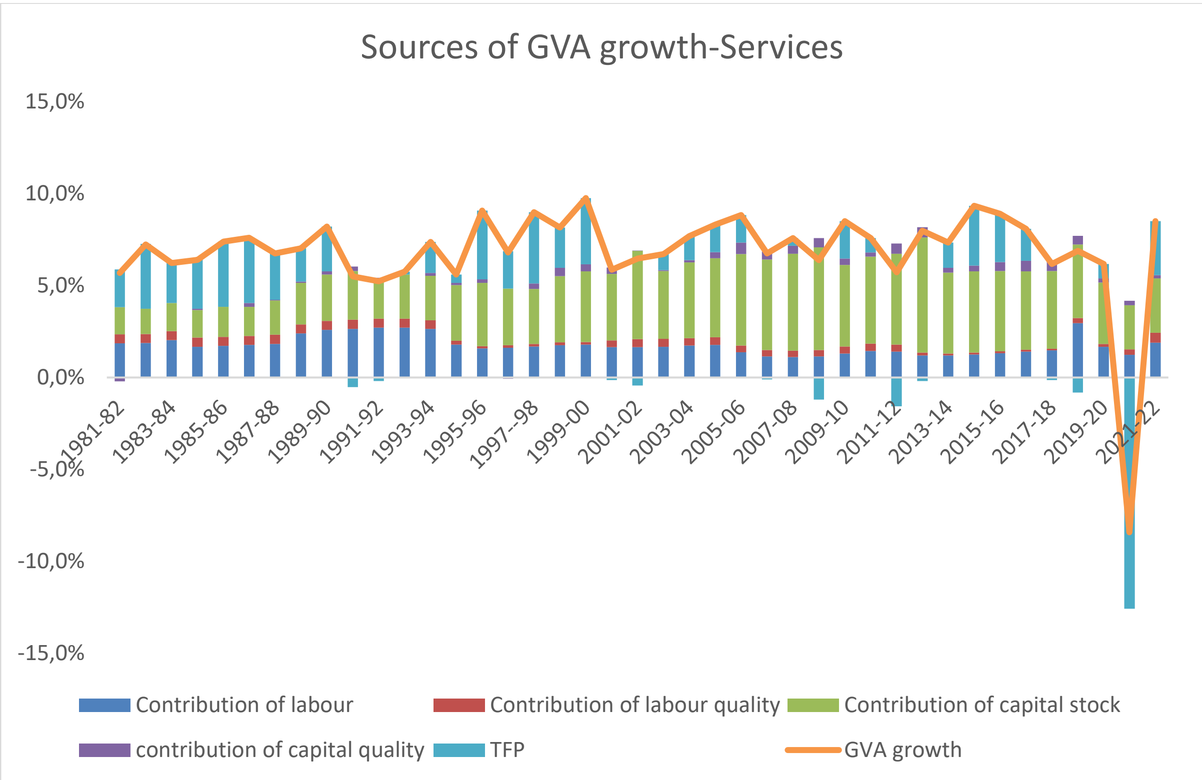
Figure
Sources of GVA growth, Manufacturing in per cent



Source: Authors computation from KLEMS data 2024

Annex II

Figure
Sources of GVA growth, Services in per cent



Source: Authors computation from KLEMS data 2024