Tracing Decomposed Income Inequality Indices in India

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Abstract

This study explores income inequality in India using data from the Periodic Labour Force Survey for 2019-20 and 2023-24, along with industry structure data from the Annual Survey of Industries 2022-23. It uses three measures of inequality, specifically the Gini coefficient, Theil indices (T and L), and the Atkinson index, to quantify and decompose within- and between-group inequalities across four socio-economic characteristics: state, gender, education level, and industry. The analysis finds that within-group inequality dominates across all these groupings, pointing to significant income disparities amongst individuals with similar backgrounds. Between-group inequality is the largest for the education and industry groupings, which points towards certain structural issues in the economy. This paper also relates within-industry inequality with the share of labour income in net value added for the formal manufacturing sector. The results show a moderately strong negative correlation between the labour intensity and inequality, offering the potential for more equitable growth. The paper provides targeted policy recommendations based on the decomposed inequality measures.

Keywords: income inequality, India, Theil index, decomposition, PLFS, labour intensity

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1 Introduction

Global income inequality has been decreasing over the past three decades, reflecting the rapid economic growth of developing nations; however, within-countries inequalities have mostly been on the rise (International Monetary Fund, 2025). This trend has also been observed in India (Bharti, Chancel, Piketty, & Somanchi, 2024), specifically after the country underwent several policy changes in the 1990s, dubbed as an ‘economic liberalisation’, that opened the country’s economy to the world and ushered in a period of accelerated economic growth as well as increasing inequalities (Acharyya, 2006). While the causes of income inequality are widely contested and multifaceted, such as the roles of technological advancement and globalisation, their consequences can be severe and far-reaching. Such inequalities have been identified as a major source of global risk in the next decade (World Economic Forum, 2024), which might have played a role in propelling social and political protests, including those in the Arab world in the early 2010s (United Nations, 2013). As inequalities create divergent life experiences and expectations within a country, certain segments of society can become disillusioned with a system that does not seem to offer them the opportunity to improve their means. Various studies have also found links between higher rates of income inequality and poorer social and health outcomes (Pickett & Wilkinson, 2015), leading to a cycle of poverty from which many find it difficult to escape without systemic support.

Though rising income inequalities are partly a consequence of the policies that enable the current global economic order and its resultant (disproportionally shared) prosperity, policymakers must find measures which simultaneously stimulate growth and strengthen social welfare. This need is particularly acute in India, which aspires to become a developed country by 2047 and to shed socio-economic disparities, including income inequalities, in line with the Sustainable Development Goals (SDGs) outlined in the 2030 Agenda for Sustainable Development. However, recent data have pointed towards worsening inequality measures: the share of the top 1% in the total income in India increased from 6.1% in 2017-18 to 6.8% in 2018-19 (Institute for Competitiveness, 2022), and inequalities further intensified by the curbs instated due to the COVID-19 pandemic (The Wire Staff, 2025).

While there have been numerous studies quantifying, tracking, and attempting to explain the sources of inequalities in India (including income and consumption inequalities at the national level and state-level comparatives of socio-economic indicators), there have only been a few studies on differentiating ‘within-group’ and ‘between-group’ income inequalities. Within-group inequalities refer to the differentials that exist between individuals of a specific subgroup, such as of the same state, gender, or education level. In contrast, between-group inequalities measure the disparity between these subgroups, such as between rural and urban populations. Decomposing income inequality indices by various subgroups of India would help better tackle within-group inequalities with targeted interventions while also providing evidence for discourse on the structural changes required to address between-group inequalities. Notably, the World Bank posited that “typically, at least three-quarters of inequality in a country is due to within-group inequality, and the remaining quarter to between-group differences” (Haughton & Khandker, 2009). Further, state-level divergences in income inequality, in conjunction with levels of welfare scheme expenditures, can also point towards measures that may have helped create a more equitable society.

2 Literature Review

The economic liberalisation in India during the early 1990s led to rapid increases in incomes and income inequality. Around 35% of national income went to the top 10% in 1987, which has risen substantially in 2022 to over 55% (Bharti, Chancel, Piketty, & Somanchi, 2024). Several studies have used decomposable inequality measures to analyse the structure of income inequality in India; one study used Theil indices and the mean log deviation to analyse district-level and rural-urban differentials (Azam & Bhatt, 2016).

Some studies have discussed the role of labour informality and spatial divergences in explaining inequality trends. India’s growth has been disproportionately driven by capital-intensive and higher-skill sectors, with limited potential for larger-scale employment generation. Gender inequality remains a structural issue in India, with women taking up relatively more informal and lower-paying jobs, even if in larger labour force participation rates than before.

This paper builds on the existing literature in three ways. First, it uses the Primary Labour Force Survey (PLFS) data for 2019-20 and 2023-24 to compute inequalities, which represent pre- and post-pandemic snapshots of the economy. Second, the study provides inequality decompositions of several population groupings (state, rural/urban, gender, education level, industry). The paper then uses these empirical findings to provide policy insights on reducing inequalities.

3 Methodology

3.1 Data Sources for Income Inequality

This study uses unit-level data from India's Periodic Labour Force Survey (PLFS) to estimate income inequality across various socio-economic groups (Ministry of Statistics and Programme Implementation, 2021). The PLFS is an annual survey conducted by the country's National Statistical Office (NSO) to estimate key employment indicators, and it provides nationally representative data on employment status, incomes, industry, and other socio-economic characteristics. While the first PLFS was for the period 2017-18[1], the focus of this study has been on the PLFS of 2019-20 and 2023-24, which can provide a snapshot of changes in inequality. This period also falls before and after the COVID-19 pandemic, and the results may pick up on its structural impacts on the economy.

The samples from the PLFS dataset were adjusted by the provided population weights and compiled as per the survey guidelines. Since this study focuses specifically on income inequalities, only those individuals engaging in economic activities under their usual status were considered. This data includes self-employed persons, workers in a household enterprise, salaried employees, and casual wage labour. It excludes any unpaid labour income, to align better with the Atkinson income inequality measure that is undefined at zero income.

The annual income is derived from one of three income sources: regular salary, self-employment, and casual wage labour. The total income is computed by annualising the reported income data. Each observation is recorded with various socio-economic characteristics for subgroup decomposition: state (covering 36 states and territories in India), sector (rural or urban), gender (male, female, other), education level (12 levels), industry classification (86 codes at 2-digit NIC), and age group (6 groups of 10-year intervals starting at 15 years old).

3.2 Measuring Income Inequality

Income inequalities capture how income is distributed in a population and can be quantified in several ways. Broadly, each measure of inequality will quantify how far away the population deviates from equal income distribution. However, each measure differs in its interpretation, sensitivity, and decomposability (Subramanian, 2011). Three income inequality indices have been measured in this study, offering different perspectives on inequalities in India:

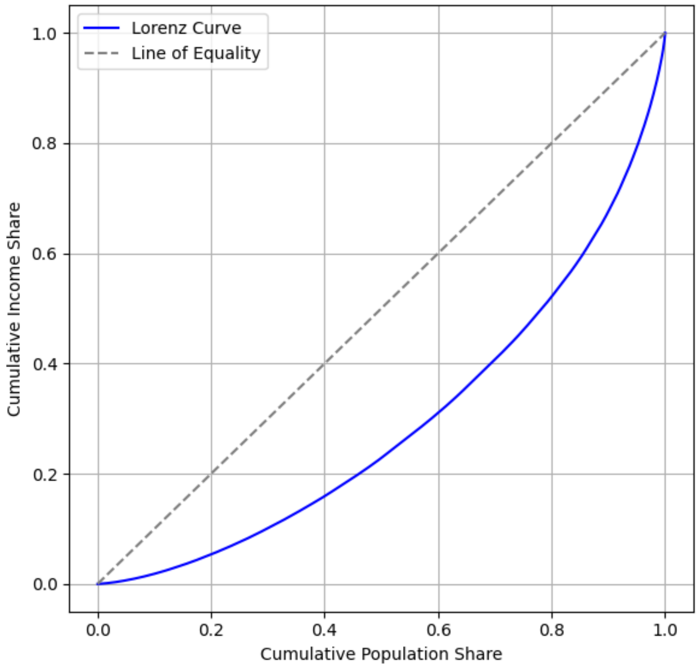
1. The Gini coefficient – a popular measure related to the Lorenz curve.
2. The Theil indices (T and L) – special cases of the generalised entropy index.
3. The Atkinson Index – this comes with a user-defined inequality aversion parameter.

[1] In India, the financial year runs from 1 April to 31 March the following year

3.2.1 The Gini Coefficient

The Gini coefficient offers an intuitive and overall view of income inequality. It measures the average difference in incomes between all pairs of individuals in a population and is bounded between 0 (perfect equality) and 1 (all income goes to one person). The Gini coefficient can be graphically represented through a Lorenz curve, which shows what share of income is earned by a given share of the population. The Lorenz curve for income in India is shown in Figure 1, along with the line of equality.

Figure 1: Lorenz Curve of Income in India 2023-24



Source: Author's computations from PLFS 2023-24

In this study, the Gini coefficient is estimated using the trapezoidal rule, which approximates the Lorenz curve with piecewise linear interpolation (Shang & Shang, 2021). It is computed as twice the area between the Lorenz curve and the line of equality. While this technique is accurate and simple to compute, it does assume linearity between consecutive data points. A major limitation of the Gini coefficient is its lack of decomposability; the Gini coefficients of subgroups cannot be summed up to give the Gini coefficient of the whole population. Additionally, the Gini coefficient is more sensitive to changes in income in the middle of the income range. It does not capture disparities in the lower or upper end as well as General Entropy (GE) indices do.

3.2.2 Theil Indices

The Theil indices are a special case of the Generalised Entropy (GE) family of inequality measures. These indices can be decomposed to analyse within- and between-group effects. There are two forms of the Theil indices: the Theil T (T_T) and Theil L (T_L) indices. These are, respectively, more sensitive to disparities at the top end and lower end of the income distribution. These have been computed using Equations (1 and (2.

$$T_T = \frac{1}{N}\sum_{i=1}^{N}\frac{x_i}{\mu}\ln\left(\frac{x_i}{\mu}\right) \tag{1}$$

$$T_L = \frac{1}{N}\sum_{i=1}^{N}\ln\left(\frac{\mu}{x_i}\right) \tag{2}$$

Where T_T and T_L are the Theil T and Theil L indices, respectively, N is the sample size, x_i is the income of individual i, and μ is the arithmetic mean.

The sources of inequalities (i.e., the within- and between-group inequalities for a chosen grouping of the population, such as state or gender) can be summed to give the national-level inequality, and the two indices can point towards which end of the income spectrum are the disparities the greatest. However, unlike the Gini coefficient, these indices are not as intuitive to grasp, given the lack of an upper bound.

3.2.3 The Atkinson Index

The Atkinson index is a measure of inequality that can be tuned to pick up disparities in a specific portion of the income distribution by varying a parameter ε. This index is based on the idea that there is a social welfare loss due to unequal income distribution, and this quantifies how much social utility can be gained by equally redistributing all incomes. Larger values of ε, the "inequality aversion parameter", lead to the index giving more weight to inequality amongst the lower end of the income distribution. The parameter ranges from 0 (no aversion to inequality) to ∞ (infinite aversion to inequality). The index ranges from 0 (perfect equality) to 1 (total inequality). In this study, a moderate ε value of 0.5 has been chosen (International Monetary Fund, 2015). While this index is useful for studying inequalities among low-income earners, it is sensitive to the inequality aversion parameter, which may be difficult to quantify.

The Atkinson index has been computed for $\varepsilon=0.5$ with Equation (3.

$$A_{\epsilon=0.5} = 1 - \frac{1}{\mu}\left(\prod_{i=1}^{N} x_i^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}} \tag{3}$$

Where A_ϵ is the Atkinson index for *ε=0.5*, μ is the mean income, and x_i refers to the income of the i^{th} individual.

4 Analysis of Results

4.1 Overall Trends in Income Inequality

The Gini coefficient at the national level in 2023-24 is 0.415, in line with other findings of income inequality in India (Rajora, 2025). While reflective of a moderate level of inequality in the workforce, it is lower than levels in 2019-20, when the Gini coefficient was 0.425. Both the T_T and T_L see reductions too (Table 1), indicating mild reductions in income inequality across the national population. The PLFS data also shows a 30% increase in nominal mean per capita income (6.8% increase in CAGR). The Atkinson index also declined, from 0.150 to 0.142, pointing to relatively faster income growth in lower-income groups.

Table 1 National-Level Inequality Measures

Inequality Measure	2019-20	2023-24
Gini Coefficient	0.425	0.415
Theil T	0.337	0.314
Theil L	0.320	0.305
Atkinson Index	0.150	0.142

Source: Author’s calculations from PLFS 2019-20 and PLFS 2023-24

4.2 National Inequalities Decomposition

Both the Theil indices can be decomposed across various population groupings and by whether the inequality stems from within groups or between groups. While this study refers mainly to the T_L decompositions, the T_T results follow similarly. The decomposition of the T_L index across the studied population groupings shows that inequality is largely driven by within-group disparities (Table 2). Industry and education level are the two groupings with the highest share of between-group inequalities (over 27% each). This indicates that the average income levels differ more across industries and education levels than across any other grouping. For example, for those with postgraduate degrees earn much more on average than those who are not literate. While the income spread within these groups is also wide, these groupings have the largest differences in subgroup average incomes.

Table 2 Within- and Between-Group Decomposition

Grouping	# of Subgroups	Share Within-Group 2023-24	Share Between-Group 2023-24	% Share Between-Group 2019-20
State	36	93.8%	6.2%	6.8%
Gender	3	92.3%	7.7%	3.9%
Sector	2	87.1%	12.9%	14.8%
Industry	86	72.6%	27.4%	26.4%
Education Level	12	72.2%	27.8%	27.7%
Age Group	6	98%	2%	1.9%

Source: Author's calculations from PLFS 2019-20 and 2023-24

High between-group inequalities point towards structural segmentation in the economy, where certain groups are receiving returns unevenly due to their socio-economic circumstance. These barriers may be addressed through policies targeting structural reforms for each grouping.

In the case of education, the relatively high between-group inequality reflects how access to higher levels of education and skilling translates to larger income gaps. For industry groupings, the level of formality of the sector, productivity levels, and its capital-intensive nature can affect wages vastly. Regional between-group inequalities reflect the nature of jobs available, which would be driven by infrastructure and resource availability in that region.

While the between-group gender inequality is relatively low, there was a marked increase compared to 2019-20, nearly doubling in its share of total inequality. Such an increase may be linked to the manner of the recovery of the job market after the COVID-19 pandemic. This increase should also be contrasted with the increase in the female labour force participation rate over the same period, from 30.0% to 41.7% (Ministry of Labour & Employment, 2024). While more women are entering the labour force, it may be into low salary or self-employed roles. This observation is reflected in the change in the share of women's self-employed or casual labour income from 41.3% to 44.7% (while men's share of income from self-employed or casual labour stayed roughly the same at 61.9%). This shift indicates that women may be participating disproportionally more in the informal sector, leading to lower incomes.

Within-group inequalities reflect income disparities for people with similar backgrounds. In contrast to the structural reforms required to address between-group inequalities, for within-group inequalities, policy interventions are more broad-based, including formalising the job market, increasing worker protection, and expanding social security.

4.3 State-Level Decomposition

The proportion of between-state inequalities remains low at 6.2%, suggesting that much of the national-level inequality comes from within states. Hence, any policy focus would have to come at the state level to tackle disparities between other subgroups in a state. A few regional trends emerge from state-level inequality measures (Figure 2, Figure 3, and Appendix A).

Some states report both a high mean per capita income (in relation to the national average) and a low Gini coefficient, such as Mizoram, Delhi, Goa, and Kerala, which suggest that there might be stronger social services, better educational outcomes, or a greater share of formal sector employment. Some states, like Bihar and Uttar Pradesh, have relatively lower Gini coefficients, largely due to uniformly low incomes. Bihar is also the only state with a negative contribution to the national Theil T index (-0.5%), due to its low mean income and low internal inequality.

There are also some large states with high per capita income, but also relatively higher income inequality, such as Maharashtra and Karnataka. These are also the two states, along with Tamil Nadu, which contribute the most to the national Theil T index, at 23.1%, 10.4%, and 9.6%, respectively. This observation is driven by both the population sizes of these states and their large urban clusters (Mumbai, Bengaluru, and Chennai) that provide both very high-income and low-income jobs.

Figure 2 Gini Coefficient by State

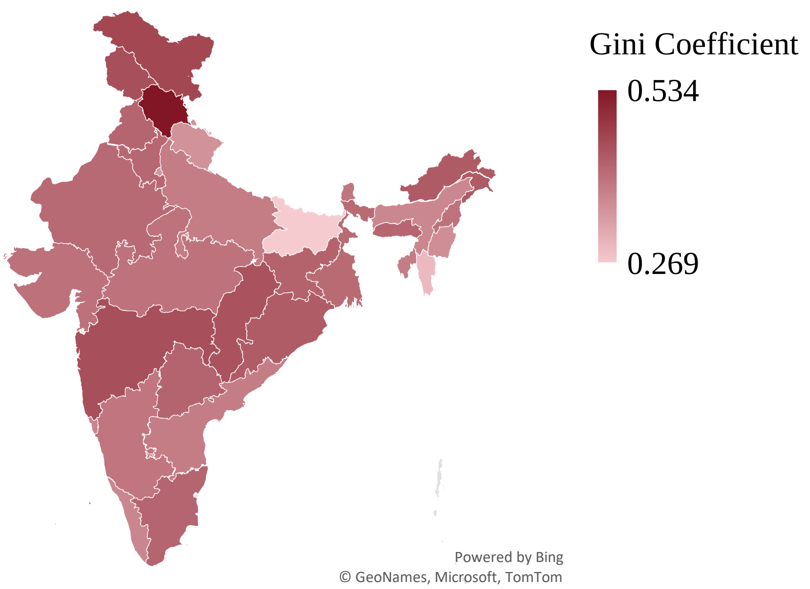
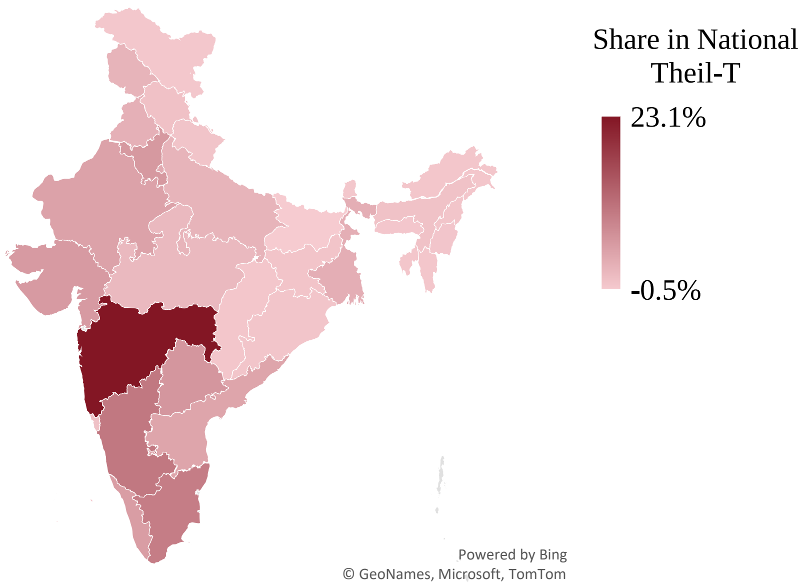


Figure 3 Share of State Inequality in National Theil T



Source: Author's calculations from PLFS 2023-24

This study investigated whether there is a correlation between a state's inequality level (through the Gini coefficient) and its share of manufacturing Gross Value Added (GVA) or services GVA in the total state GVA. These correlations were found to be weak and statistically insignificant. Similarly, the correlation between the share of income from salary and the Gini coefficient is also modest, which indicates that a larger share of people working in a formal sector may not be the only driver of reducing inequalities.

4.4 Industry-wise Decomposition

Industry-wise decomposition shows that this grouping is one of the strongest structural drivers of income inequality in the country – between-industry inequality accounts for 27.4% of national inequality, one of the highest between-group shares amongst all the population groups studied. The industry-wise wage differentials are driven by the formality of the sector, its productivity, and labour intensity.

The share of between-group inequality is higher in T_T, which is more sensitive to high-end income disparities than they are in T_L. This is particularly the case for industries like financial services, IT services, and education, given their substantially higher incomes than those in sectors like agriculture or construction. These sectors are also relatively formalised, with some of the highest shares of regular salary income to total income. While the between-industry inequalities highlight the market power of certain sectors, the within-industry inequality component is the most dominant, accounting for 72.6% of total inequality across all industries. There exist large income variations within each industry group, particularly in agriculture, retail trade, and construction. These sectors are also some of the least formalised, with the lowest shares of regular salary income of all industries.

Table 3 Industries Contributing to National Inequality

Largest Contributors to T_T		**Largest Contributors to T_L**	
Sector	**% Share in Total National Inequality**	**Sector**	**% Share in Total National Inequality**
Education	18.8%	Crop and animal production, hunting and related service activities	71.5%
Computer programming, consultancy and related activities	18.8%	Construction of buildings	15.0%
Public administration and defence; compulsory social security	13.1%	Manufacture of wearing apparel	5.6%
Human health activities	6.9%	Retail trade, except of motor vehicles and motorcycles	4.4%
Financial service activities, except insurance and pension funding	6.7%	Manufacture of tobacco products	3.1%

Source: Author's calculations from PLFS 2023-24

Interestingly, while a higher share of regular salary income (a proxy for the formality of a sector) does tend to lead to lower within-group inequalities, this does not hold for the education and health sectors. While being relatively more formal sectors, they also have the largest within-group income inequalities. Conversely, the real estate sector, though being highly informal, has relatively low within-group inequalities.

The decomposition of Theil indices by major industry groups (primary, secondary, and tertiary sectors) is provided in Table 4. These results highlight the role the tertiary sector plays in driving income inequality at the national level at the upper end of incomes (Theil T). In contrast, the primary sectors contribute a substantial 72.5% to Theil L due to lower-end income inequalities consistent with low-productivity and informal industries. Negative values indicate that the sector reduces inequality: primary sectors have widespread low incomes and minimal earners, so pulls down T_T. In contrast, the tertiary sector's low-income spread is less prominent than in other sectors.

Table 4 Share of Theil Inequality by Industry Groupings

Industry Grouping	% Share of Theil-T in National Inequality	% Share of Theil L in National Inequality
Primary Sectors	-8.5%	72.5%
Secondary Sectors	13.5%	28.2%
Tertiary Sectors	95.0%	-0.7%

Source: Author's calculations from PLFS 2023-24

4.5 Impact of Labour Intensity on Inequalities

For further analysis of the structural drivers of within-industry inequalities, a sector-wise labour intensity metric was computed using data from India's Annual Survey of Industries (ASI) for 2022-23[2] (Ministry of Statistics and Programme Implementation, 2024). This analysis focuses on NIC 2-digit codes 10-33 (for a total of 24 sectors analysed in this section), which represent the organised manufacturing sectors in India. The ASI covers only the organised sector, and unregistered small manufacturing units are not accounted for. This may lead to an underestimation of inequality in sectors with a high degree of informality.

The aim of this analysis is to understand whether inequality patterns across industries can somewhat be explained by the way value add is distributed between the labour and capital factors of production. Three labour-intensity metrics are considered in this study, each normalised against the sector's Net Value Added (NVA), and are correlated with sectoral Gini coefficients (Table 5):

1. Workers per unit of NVA
2. Total persons engaged (workers + supervisors + unpaid family members) per unit of NVA
3. Share of Labour income in NVA

Table 5 Impact of Labour Intensity on Sectoral Inequality

Labour Intensity Measure	Correlation with Gini
Workers / NVA	-0.373
Total Persons Engaged / NVA	-0.434
Labour Income / NVA	-0.631

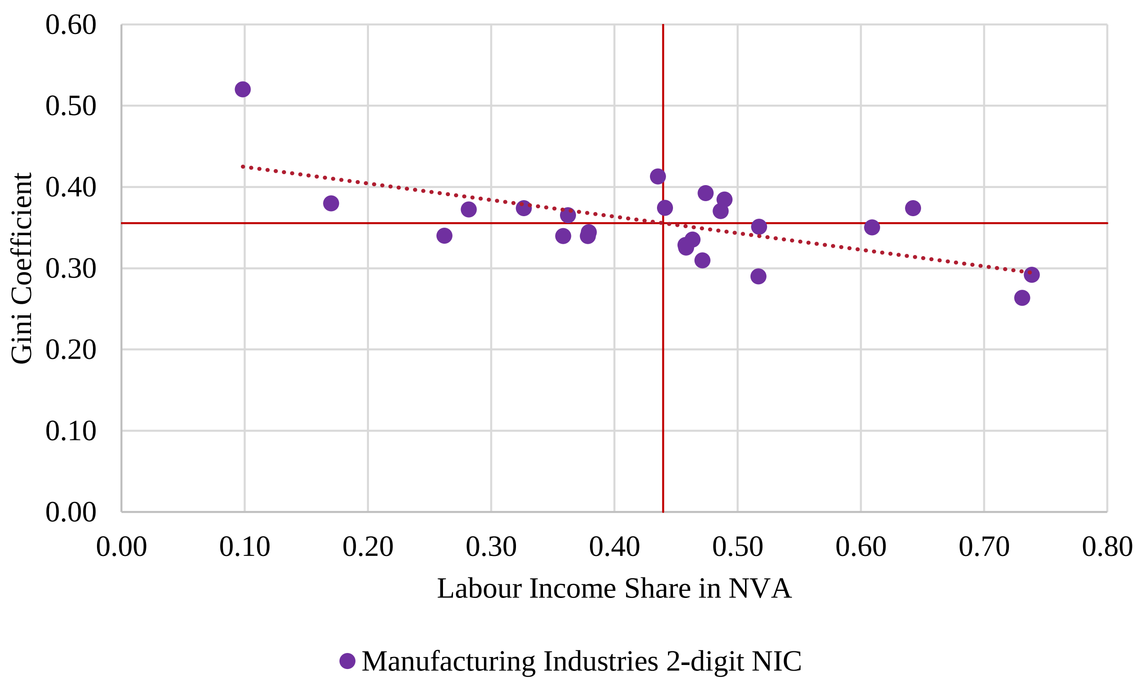
Source: Author's calculations using PLFS 2023-24 and ASI 2022-23

[2] ASI 2023-24 has not yet been published

The ratio of workers employed to NVA reflects how labour reliant the sector is, and this metric was found to have a moderate negative correlation of -0.373 with the sectoral Gini coefficient. When this ratio was expanded to include all employment in the sector (workers, supervisors, and unpaid family workers), the correlation strengthened to -0.434. These results show that sectors which can absorb larger numbers of people, across various levels, tend to have a lower within-industry income inequality. This may be reflective of large numbers of people employed at standardised wage rates, or flatter organisational hierarchies.

The ratio of labour income to net value added consists of all payments made as wages and salaries, and reflects how much of the value add is returned to the labour factor of production. It has a much stronger negative correlation of -0.631 with sectoral Gini coefficients. This suggests that industries that are more labour-intensive tend to have lower income inequality. The sector-wise Gini coefficients and labour income share in NVA is mapped in Figure 4, with four quadrants defined by the mean Gini coefficient (0.36) and labour income share (0.44) of these 24 sectors.

Figure 4 Gini Coefficient versus Labour Income Share in NVA by Manufacturing Sectors at 2-digit NIC



Source: Author’s calculations using PLFS 2023-24 and ASI 2022-23

The 24 sectors are categorised in four quadrants, depending on their level of labour income share in NVA (LIS) and inequality (Gini). The interpretation of these quadrants, examples of a sector in each quadrant, and the employment share in each quadrant is provided in Table 6. Notably, almost 38% of all organised sector manufacturing jobs are in industries categorised in the fourth quadrant, which represents high shares of labour income in NVA with low inequality.

Table 6 Classification of Industries by Labour-Intensity and Inequality

Quadrant	Interpretation	% Share in Employment	No. of Industry Groups & Example
1	High LIS, high Gini: Disparate wage structures	23%	5 groups including: Wearing apparel; Machinery & equipment
2	Low LIS, high Gini: Capital-intensive	28%	6 groups including: Basic metals; Chemicals
3	Low LIS, low Gini: Capital-intensive, potential wage compression	11%	4 groups including: Other non-metallic products; Paper and paper products
4	High LIS, low Gini: Labour-intensive with low income disparity	38%	9 groups including: Food products; Textiles

Source: Author's elaboration

This analysis underscores the role of labour intensity in impacting inequality within the organised manufacturing sector. Policies should promote the growth and expansion of sectors in lying in the fourth quadrant, such as the manufacture of food products, textiles, and fabricated metal products. Incentives may be provided to firms that have a higher share of labour income in NVA. Vocational training can be targeted towards teaching the skills required to work in industries in this quadrant.

4.6 Education-level Decomposition

The education level of an individual is one of the biggest structural factors that impact income inequality; 27.8% of T_L is due to between-education-level differences, the highest of any other grouping studied. While an individual educated up to the primary level might earn 25% less than the mean national income, a graduate earns around 86% more. However, the within-group component still dominates. Even amongst people in the same education group, income disparities are large and tend to be higher at either end of the education level. With the illiterate to primary education level groups, income inequalities might arise due to the mix of casual labour in different informal sectors. Among the highly educated groups, rising inequality may be reflective of limited access to high-paying jobs in the formal sector. It may also point towards underemployment and a need to encourage alternative training options to fit the requirements of the labour market.

These findings show that the labour market is segmented by the level of education attained – those who have finished their secondary education (i.e., the last two years of schooling) tend to earn more than the national average.

Table 7 Education-level Decomposition

Education Level	Gini Coefficient	% Salary Income in Total Income	Ratio of Mean Income to Mean National Income
Not literate	0.345	10%	0.61
Literate without formal schooling	0.325	15%	0.64
Below primary	0.328	14%	0.71
Primary	0.321	18%	0.75
Middle	0.322	25%	0.83
Secondary	0.346	32%	0.97
Higher secondary	0.365	42%	1.08
Diploma/certificate course	0.369	70%	1.51
Graduate	0.399	70%	1.86
Postgraduate and above	0.379	82%	2.50

Source: Author's calculations from PLFS 2023-24

Note: 'Teaching & Learning Centre' and 'Other' education groups have been omitted due to their low population sizes.

5 Discussion of Results

5.1 Policy Implications

The previous section has shown that while overall income inequality has declined slightly between 2019-20 and 2023-24, various structural disparities remain, particularly between industries and between education levels. Within-group inequalities are consistently higher than between-group inequalities for all studied groupings, which points towards lasting segmentations in the labour market. A key finding of this paper is the moderately strong correlation between labour income shares in net value added and within-industry inequality in the formal manufacturing sector.

This section outlines some policy implications arising from the findings, addressing both within-group and between-group inequalities.

Policy Area	Implication	Rationale

Addressing within-group inequalities	Specify a minimum wage	Setting and enforcing minimum wages across all industries, especially those with a higher share of casual labour income, compresses wage distributions and reduces income inequality at the low end.
	Promote formalisation	The by-industry analysis showed that sectors that were more formalised (i.e., paying a greater share of income through regular salaries) tended to have lower inequality. This may be due to contractual and other labour protections that are offered when working in the formal sector.
	Support labour-intensive and low inequality industries	This study finds a moderately strong correlation between labour-intensity and lower inequality. Inequality does not need to be a trade-off for growth. There should be policy support to such firms, perhaps in the form of incentives.
	Match skills with employment	Skill alignment schemes can help address underemployment to address higher inequalities amongst the highly educated groups. Additionally, education outcomes at a higher level should be better aligned with labour market requirements.
Addressing between-group inequalities	Delink education level from earnings	The analysis shows that higher education levels lead to higher average salaries. Promoting alternate options to higher education can help delink education level with incomes. Vocational training and apprenticeships can be better linked with industry demands.
	Encourage cross-sector mobility	Due to market forces, some sectors can offer higher wages than others. Implementing re-training schemes, for example, can help individuals move towards higher-income sectors.
	Enhance social infrastructure	Between-gender income inequalities have risen between 2019-20 and 2023-24, which may point to increasing barriers for women. While the female labour force participation rate has increased, it has been relatively more in low-income jobs. Formalising female-dominated sectors and providing more flexibility with work can help women address income disparities.

Source: Author’s elaboration

5.2 Limitations of the Study

Some of the limitations of this study relate to the use of the PLFS data to compute income inequalities. Firstly, incomes are restricted to only earned incomes from participating in the workforce and do not include earnings from pensions, remittances, or rents. Excluding these earnings would likely lead to an underestimation of income concentration at the top end. Secondly, the PLFS relies on self-reporting of incomes for either the preceding month (salary and self-employment earnings) or the preceding week (casual labour wages); there may be seasonal variations, particularly for casual labour, which are not reflected in this analysis. Thirdly, incomes are not adjusted for the cost of living in the region and might overstate inequalities between high-cost urban areas and low-cost rural areas. Limitations of the ASI data have been discussed in Section 4.4.

6 Concluding Remarks

This paper provides a comprehensive assessment of income inequality in India using PLFS data for 2019-20 and 2023-24, along with industry structure information from ASI 2022-23. The Theil inequality indices are decomposed across various socio-economic groups, as well as by within- or between-group inequalities. The analysis of the decompositions has been used to identify some policy priorities to reduce inequality.

The findings in the study show that within-group inequalities dominate across all the analysed socio-economic groups, implying that the labour market is fragmented even for people with similar backgrounds. Education level and industry classification exhibit the highest between-group inequality, due to the structural barriers in the economy. At the state level, within-group inequality dominates, and further studies would be required to determine the sources of intra-state disparities.

A major contribution of this paper is connecting income inequality with the labour-intensity of a manufacturing industry. The study finds a moderately strong negative correlation between the share of labour income in net value added and the Gini coefficient of the formal manufacturing sector. This indicates that inequality does not necessarily need to be a consequence of growth. To tackle income inequality in India, this study highlights the need to promote the development of such sectors, along with reforming certain structural barriers in the economy.

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8 Appendix

Appendix A: State-level Gini Coefficient in 2023-24

State	Gini Coefficient
Himachal Pradesh	0.534
Andaman & Nicobar Islands	0.462
Ladakh	0.461
Jammu & Kashmir	0.451
Maharashtra	0.450
Puducherry	0.447
Chhattisgarh	0.444
Arunachal Pradesh	0.433
Odisha	0.431
Jharkhand	0.421
Telangana	0.420
Punjab	0.419
Tamil Nadu	0.418
Chandigarh	0.418
Meghalaya	0.416
Haryana	0.415
Rajasthan	0.411
West Bengal	0.410
Lakshadweep	0.409
Gujarat	0.400
Nagaland	0.399
Madhya Pradesh	0.398
Karnataka	0.394
Sikkim	0.394
Uttar Pradesh	0.385
Tripura	0.384
Andhra Pradesh	0.384
Dadra & Nagar Haveli and Daman & Diu	0.383
Goa	0.373
Kerala	0.370
Assam	0.369
Manipur	0.358
Uttarakhand	0.353
Delhi	0.349

Mizoram	0.293
Bihar	0.269

Source: Author's calculations from PLFS 2023-24