Employment Status and Wage Gap of Youth Engaged in Decent vs Non-Decent Work in India

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Between 2017–18 and 2023–24, the youth workforce participation rate (WPR) in India increased significantly, accompanied by a substantial decline in the unemployment rate. Over the same periods, the proportion of young individuals engaged in regular wage and salaried employment (RWSE) was consistently higher than that of the overall working-age population. Indicators of decent work, such as access to written contracts, paid leave, and social security coverage, show notable improvements, pointing to the gradual formalisation of youth employment and the expansion of labour market protections. These trends collectively suggest that, alongside rising participation, the overall quality of employment opportunities available to youth has improved over time. The primary objective of this study is to examine the employment status of young people and analyse wage disparities between decent and non-decent workers. In addition, the study evaluates the wage penalty associated with participation in non-decent work activities, thereby contributing to a more profound understanding of labour market inequality. The findings reveal that the wage penalty for non-decent employment is not evenly distributed across the wage spectrum; rather, it is more pronounced at the lowest and highest wage quantiles. The study also found that the magnitude of this penalty has declined over time, suggesting gradual improvements in the relative position of non-decent workers.

Keywords: Youth, Labour, Wage Penalty, Decent Work, Skill Level, Returns to Education

JEL Codes: J13, J40, J31, J81, J24, I26

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1. Introduction

Labour market dynamics vary markedly across economic contexts. Stable institutions and comprehensive labour market regulations support the considerable uniformity and formality of employment structures in developed economies. By contrast, labour markets in developing economies exhibit pronounced heterogeneity and informality, which is reflected in diverse employment patterns, unequal access to jobs, wage disparities, and inconsistent income security and job stability (Dewan & Peek, 2007). Many developing countries share characteristics of widespread underemployment, and limited industrialisation (Ghai, 2002). The expansion of global production has generated employment opportunities in developing economies; while some roles offer good wages and require specialised skills, a substantial proportion are low-skilled, casual positions with poor working conditions, low pay, and insecure informal arrangements that lack legal and social protection (Barrientos et. al., 2011). Consequently, most workers in these contexts engage in vulnerable employment without social protection, secure contracts, paid leave or insurance (Moktan, 2019). Labour market inequality is evident across sectors, wages and earnings, work quality, labour market access, and the organized-unorganized divide (Dev, 2018).

Because labour markets are complex, the International Labour Organisation (ILO) introduced the idea of ‘decent work’ in 1999, defining it as "employment that upholds freedom, equity, security, and human dignity while ensuring fundamental rights, fair remuneration, and social protection." The definition has become a useful framework for examining working conditions and guiding more inclusive, sustainable employment policies. Researchers across disciplines have developed practical, context aware ways to measure decent work in different settings. Several key indicators are fundamental to an understanding of decent work, including employment availability, job security, respect for rights and dignity, and opportunities for meaningful participation in the workplace (Fields, 2003). Social protection is central to the concept: it reduces worker vulnerability and helps secure social and economic well-being, for example by preventing work related accidents, illness and disability, regulating working hours, and guaranteeing adequate rest and holiday entitlements (Sengenberger, 2001). Freedom of association is also recognised as a key indicator (Ghai, 2002; Fields, 2003). Beyond these core elements, scholars have proposed an expanded set of indicators to capture decent work’s multidimensional nature, including adequate financial security at work encompassing health protection, pensions and livelihood support (Anker et. al., 2002); fair hourly pays and limits on excessive working hours; measures to promote youth employment and gender equality in

labour force participation (Bescond et. al., 2003); and clear workplace principles, manageable workloads and meaningful remuneration (Ferraro et. al., 2018). In 2012, the ILO identified ten substantive elements as key indicators: employment opportunities; adequate earnings and productive work; decent working time; work–life balance; elimination of unacceptable forms of work; employment stability and security; equal opportunity and treatment; a safe working environment; access to social security; and effective social dialogue and representation for employers and workers (Moktan, 2019).

In alignment with the ILO's decent work agenda, the Government of India implemented its inaugural Decent Work Country Programme (DWCP) for 2007–2012, marking a formal policy commitment to harmonise national labour frameworks with international labour standards. The programme prioritised the promotion of productive and decent employment for both women and men, with particular emphasis on youth and other vulnerable population groups. It sought to extend social protection, eliminate unacceptable forms of work, and eradicate child labour. These objectives were framed as mechanisms to foster inclusive growth, mitigate labour market inequalities, and uphold fundamental labour rights across both the formal and informal sectors. The subsequent DWCP (2013–2017) sought to deepen these aims by enhancing labour market inclusivity and resilience, concentrating on the expansion of decent and productive employment for women, youths, and marginalised groups. Core strategic interventions included the promotion of formalised informal employment, the strengthening of labour institutions, and the extension of social security coverage, especially for informal sector workers who constitute a substantial share of India’s workforce. Together, the two DWCP cycles represent a policy trajectory focused on addressing structural vulnerabilities in the Indian labour market, whereas persistent implementation and coverage challenges continue to shape outcomes.

Building on earlier initiatives, India’s third DWCP (2018–2022) articulated a forward-looking agenda to foster a more equitable and productive future of work. Its core objectives included promoting high quality job creation and facilitating the transition from informal to formal employment; the programme was explicitly aligned with the Sustainable Development Goals and sought to enhance gender equity, productivity and social cohesion across the economy. The DWCP for India (2023–2027) refines this trajectory by delineating three principal priorities: firstly, to promote adherence to international labour standards and the fundamental principles and rights at work, strengthen social dialogue and assist constituents in crafting effective policy responses; secondly, to ensure full and productive employment and decent

work for all, encompassing measures for formalisation and equitable transition; and thirdly, to strengthen institutions that empower workers, particularly marginalised and vulnerable populations, to improve employment outcomes and progressively achieve universal social protection. Collectively, these priorities signal a policy emphasis on institutional capacity building and comprehensive social protection strategies to support inclusive labour market transformation.

Regular wage and salaried employment (RWSE) are conventionally regarded as higher quality work because it is more likely to provide stable earnings, contractual protections, adherence to labour standards and access to social protection (Fields, 2011). Conceptually, RWSE corresponds to the ILO's decent work paradigm, which emphasises productive, secure and rights respecting employment (Mamgain & Tiwari, 2017; Srivastava, 2012). Nevertheless, evidence from India demonstrates that a substantial fraction of nominally regular employment is characterised by intra-category informality; precarious contractual arrangements and weak tenure security; substandard working conditions; low remuneration relative to living costs; and restricted access to social insurance, paid leave and other statutory entitlements (Mamgain & Tiwari, 2017). This persistence of informality within RWSE undermines the anticipated welfare and productivity gains of formal employment and complicates policy efforts to promote formalisation, expand social protection and reduce labour market inequality.

India possesses one of the youngest populations globally, a demographic endowment that presents both potential economic gains and substantial policy challenges. According to the Youth India Report (2022), 27.2 per cent of the population in 2021 were aged 15–29 years; the Periodic Labour Force Survey (PLFS), 2022–24 estimates approximately 308 million individuals in this cohort, or roughly 26 per cent of the population. Notwithstanding the fact that youth constitute about one quarter of the population, existing research and policy discourse in India has predominantly addressed aggregate labour market indicators, often neglecting the age specific constraints that shape youth labour market transitions. Youth employment is a critical determinant of individual welfare and macroeconomic outcomes; successful transitions to productive, decent employment contribute to the realisation of the demographic dividend, sustained economic growth, and social stability. Empirical evidence remains limited and fragmented regarding the incidence of decent work, youth engagement in RWSE, and the distributional implications for wages. To address this gap, the present study evaluates key decent work indicators among youth in RWSE, assesses wage differentials between workers in

decent and non-decent employment across educational and skill levels, and quantifies the wage penalty associated with non-decent employment across the wage distribution.

This paper is organised as follows. Section 1 introduces the research gap, motivations, and contributions to the literature. Section 2 describes the data sources and the econometric tool employed. Section 3 presents descriptive evidence on the incidence and quality of decent-work indicators among youth engaged RWSE. Section 4 estimates wage differentials between workers in decent and non-decent employment, examines heterogeneity across worker characteristics, and quantifies the wage penalty associated with non-decent employment across the wage distribution. Section 5 concludes by summarising the principal findings.

2.1. Data Sources and Sample

The definition of 'youth' is not uniform across countries or international institutions, reflecting differences in demographic structure, socio-economic context and policy priorities. The United Nations typically classifies youth as individuals aged 15–24 years; UN-Habitat extends this range to 15–32 years, while the African Youth Charter adopts a still wider bracket of 15–35 years[1]. National definitions also vary and have evolved over time: India's inaugural National Youth Policy (1988) defined youth as those aged 15–35 years, the 2003 policy revised this to 13–35 years, and the 2014 policy narrowed the cohort to 15–29 years to better align with contemporary demographic and policy considerations. These definitional divergences have material implications for measurement, cross-country comparability and the targeting of labour market and social protection interventions. For the present study, 'youth' is defined as individuals aged 15–29 years, in accordance with India's National Youth Policy (2014).

The present study is based on the PLFS data conducted by the National Sample Survey (NSS) of India. PLFS provides comprehensive information on labour market conditions across all states and union territories. A key advantage of this dataset is its annual coverage from July to June, along with a large and nationally representative sample size. The surveys provide detailed information on the employment situation in India, including both Usual Principal Status (UPS)[2] and Usual Subsidiary Status (USS) activities[3]. The employment status in present paper is

[1] https://www.un.org/esa/socdev/documents/youth/fact-sheets/youth-definition.pdf.

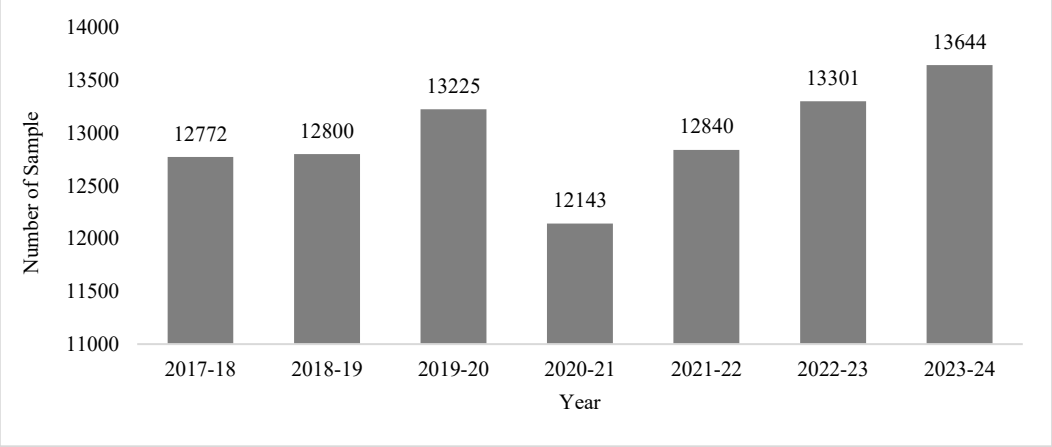
[2] The activity status on which a person spent a relatively long time (major time criterion) during 365 days preceding the date of the survey was considered as the usual principal activity status of the person.

[3] The activity status in which a person, in addition to his/her usual principal status, performs some economic activity for 30 days or more for the reference period of 365 days preceding the date of the survey was considered as the subsidiary economic status of the person.

calculated based on UPS and the USS most commonly calls the usual status (US). The survey also offer data on employment classification according to the National Classification of Occupations (NCO)[4] of India.

The NSS defines RWSE as those who worked in either farm or non-farm activities and, in return, received salary/wages on a regular basis. Such employment is typically expected to satisfy the fundamental criteria of decent work as articulated by the ILO, including fair remuneration, job security, access to social protection, and the safeguarding of workers' rights. The NSS's principal advantage for analysing employment quality lies in its large, nationally representative sample, which enhances the reliability and generalisability of empirical estimates. By contrast, the PLFS provides more timely and frequent microdata but is limited in its assessment of decent work. The survey records only a restricted subset of indicators and therefore cannot capture the full multidimensionality of the ILO framework. Notwithstanding these limitations, the PLFS does include a set of core variables commonly used to measure decent work. Drawing on the literature and the PLFS schedule, this study employs three observable indicators as operational criteria for decent work: (i) the existence of a written contract, (ii) access to paid leave, and (iii) entitlement to social security benefits. Consistent with this operation, workers satisfying all three conditions are classified as engaged in decent work, whereas the absence of all the three indicators denotes non-decent employment.

Figure 1: Sample size[5] of youth engaged in RWSE earning activities



Source: Different rounds of NSS-PLFS unit-level data.

[4] The National Classification of Occupations (NCO) is a systematic framework for classifying all jobs and occupations in the Indian labour market. It establishes and maintains occupational standards in the country and is regularly used within the network of employment exchanges that constitute the public employment service, particularly for the purposes of occupational classification, job postings, and job

[5]The sample comprises individuals between 15 and 29 years of age.

The analysis uses seven rounds of unit level microdata from the PLFS, covering the period 2017–18 to 2023–24. The paper restricts the sample to individuals aged 15–29 who are in RWSE. Descriptive analysis is produced using the PLFS sampling weights to generate nationally representative estimates; where relevant, variance estimates are computed to reflect the survey's complex design. Figure 1 presents the sample size of youth in RWSE across the PLFS rounds.

2.2. Model Specification and Estimation Process

The study uses an ordinary least squares (OLS) cross sectional regression model to estimate the wage penalty associated with participation in non-decent work. The OLS estimation captures the mean wage penalty associated with non-decent work participation.

$$\ln (W_i) = \alpha_i + \beta_i D_i + X_i \gamma_i + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots (1)$$

$\ln (W_i)$ represents the log-transformed wage/salary of both decent and non-decent workers, and α_i denotes the content term. D_i is a dummy variable that takes the value 1 if the worker is in non-decent employment and 0 if the worker is in decent employment. The coefficient β captures the wage penalty associated with participation in non-decent work. X_i is the vector of control variables that influence the wage of the i^{th} worker, and γ_i represents the vector coefficients of other control variables. Finally, μ_i is the error term that accounts for unobserved factors affecting wages.

A major limitation of the OLS regression model is that it estimates only the average effect of non-decent work, potentially masking how the wage penalty varies across the wage distribution. In equation (1), the dependent variable is heterogeneous, meaning their relationship with explanatory variables may differ at different points of the distribution. Under such conditions, OLS cannot accurately capture the wage penalty for non-decent workers at the lower, median, or upper ends of the wage spectrum, making it unsuitable for analysing wage heterogeneity.

To capture this heterogeneity a condition quintile regression model (CQRM) is used in the study CQRM is the natural extension of the OLS estimate of the conditional mean but give the coefficient of the independent variable against dependent variable at different quintile level (Koenker & Bassett, 1978). Another advantage of the quantile regression model is its robustness to outliers in the dependent variable, which is especially valuable in wage analysis,

where extreme values can skew mean-based estimates (Buchinsky, 1998). Martin & Pereira (2004) present the typical quintile regression model in the following form.

$$\ln (W_i) = Xi\beta_{\Theta} + \mu_{\Theta i,}$$

$$\text{with } Q_{\Theta} = [\ln (W_i) \mid X_i] = \alpha_{i\Theta} + \beta_{i\Theta} D_i + X_i\gamma_{i\Theta} + \mu_{i\Theta} \ldots\ldots\ldots (2)$$

In the quantile regression framework, ln (W_i) denotes the log of the wage/salary for both decent and non-decent workers. D_i is a dummy variable that takes the value 1 if the worker is in non-decent employment and 0 if in decent employment. B_θ represents the coefficient of D_i estimated at the θ^{th} quantile of the wage distribution, while γ_θ denotes the vector of coefficients for other control variables at the same quantile, and μ_θ is the error term. In this study, quantile regression is estimated at multiple points across the wage distribution—specifically at the 10^{th}, 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles (θ = 0.10p, 0.25p, 0.50p, 0.75p, 0.95p) to capture the heterogeneous effects of non-decent work participation on wages across different segments of the wage spectrum.

In the regression model (2), a potential concern may arise due to sample selection bias in the wage equation, which may affect the robustness of the quantile regression estimates. To address this issue, it is necessary to account for possible selections in employment or types of work. The classic two-step correction procedure proposed by Heckman (1979) and further discussed by Bosio (2009) provides a foundation for addressing such bias. Building on this framework, Buchinsky (1998, 2001) extended the Heckman approach to the context of quantile regression by introducing a two-step semi-parametric method.

In the first step, a probit model is estimated to predict the probability of selection into the sample (e.g., participation in decent or non-decent employment). The equation of the probit regression model as mentioned in Maddala (1983) is written as follows:

$$Y_i^{*} = \beta X_i + \mu_i \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

$$Y_i^{*} = \beta_0 + \sum_{j=1}^{k} \beta i\, X_{ij} + \mu_i$$

Where Y* = is an unobserved dependent variable or latent variable. X_i for observation *i*. The probit model includes six continuous and categorical covariates: gender, sector, vocational/technical training status, education level, caste category, and skill level category. β_i is the vector of parameters, and μ_i is the error term.

The observed outcome Y_i (participation in non-decent work) is related to the latent variable as

$$Y = 1, \text{ if } Y_i^* > 0, \text{ participate in non-decent work activity}$$

$$Y = 0, \text{ if } Y_i^* < 0, \text{ participate in the decent work activity}$$

Hence the model-implied probability of $Y_i = 1$ is

$$\Pr(Y_i = 1 | X_i) = \Pr[\mu_i > -(\beta_0 + \sum_{j=1}^{k} \beta_i X_{ij})]$$

$$= \Phi(\beta_0 + \sum_{j=1}^{k} \beta_i X_{ij})$$

- where $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF).

After the estimation of probit regression, the Inverse Mill Ratio (IMR) is generated. This is the ratio of the standard normal Probability Density Function (PDF) to the standard normal Cumulative Density Function (CDF). In the second step, the IMR is used as an additional regressor for the quintile regression. If the IMR is significant, it is normally considered that there is sample selection bias in the regression model.

So final CQRM after inclusion of IMR as an addition regressor as is presented by equation (4)

$$Q_\Theta = [\ln(W_i) | X_i] = \alpha_{i\Theta} + \beta_{i\Theta} D_i + X_i \gamma_{i\Theta} + \delta\lambda_{i\Theta} + \mu_{i\Theta} \ldots\ldots\ldots (4)$$

where λ shows the IMR

Table 1: Description of the independent variables

Variable name	**Variable Type**	**Description of the variables**	**Variable Categories**
Worker Type	Binary	Decent Worker-0 ® Non-Decent Worker-1	Labour Market
Gender	Binary	Male Worker-0® Female Worker-1	Demographic
Sector	Binary	Rural - 0® Urban -1	Geographical
Social Group	Binary	Non-SC/ST-0 SC/ST-1	Socio-economic
Vocational Training	Binary	Worker received vocational training -0® Worker not received vocational training-1	Skill

Variable name	Variable Type	Description of the variables	Variable Categories
Education	Categorical	Illiterate-0® Education up to Secondary-1 Higher Secondary with Diploma & Certificate Course -2 Graduation & Above-3	Education
Skill Level [6]	Categorical	Skill level-0® Skill level-1 Skill level-2 Skill level-3	Skill

® is the reference category

3. Performance and Trend of Decent Work Indicators

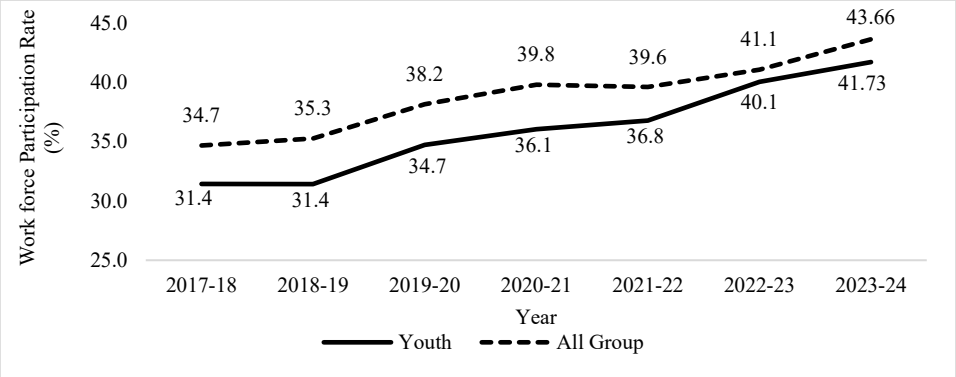
The total workforce participation rate in India increased from 34.69 per cent in 2017–18 to 43.66 per cent in 2023–24, reflecting an annual growth rate of 3.91 per cent, largely due to a significant decline in the unemployment rate. Similarly, the youth workforce participation rate, which stood at around 31 per cent in 2017–18, rose sharply to 42 per cent in 2023–24, recording an annual growth rate of 4.84 per cent, driven by an annual decline of -8.89 per cent in the youth unemployment rate (Figure 1 & Figure 2). Notwithstanding these gains, the youth unemployment rate remains roughly three times the overall rate, indicating persistent barriers to youth labour market integration.

Structural determinants of this disparity include pronounced skill mismatches between the competencies of young entrants and evolving labour market demand, geographic and locational constraints to job access, the prevalence of outdated or non-transferable skills, and limited prior work experience. These factors restrict access to stable, quality employment and channel a substantial share of youth into low quality, insecure jobs with weak contractual protections and limited social security coverage. The consequent excess supply of youth labour places downward pressure on wages and non-wage benefits, thereby reinforcing the observed deficits in employment quality.

The share of youth in RWSE has remained higher than that of the aggregate workforce throughout 2017–18 to 2023–24. In 2017–18, 29 per cent of youth were employed in RWSE compared with 23 per cent of all age group; by 2023–24, these figures declined only marginally to 27 per cent and 22 per cent, respectively (Figure 3).

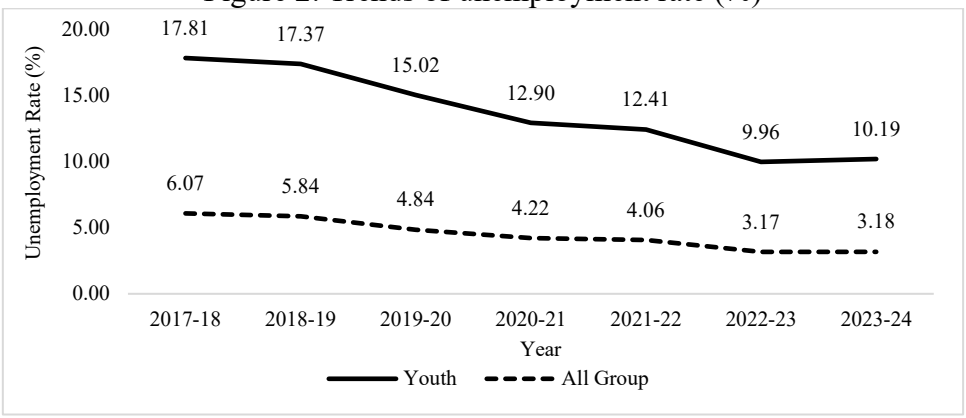
[6] Skill level 0 includes professionals. Skill level 1 encompasses elementary occupations. Skill level 2 covers clerks, service workers, shop and market sales workers, skilled agricultural and fishery workers, craft and related trades workers, plant and machine operators and assemblers. Finally, skill level 3 pertains to associate professionals.

Figure 1: Trends of workforce participation rate (%)



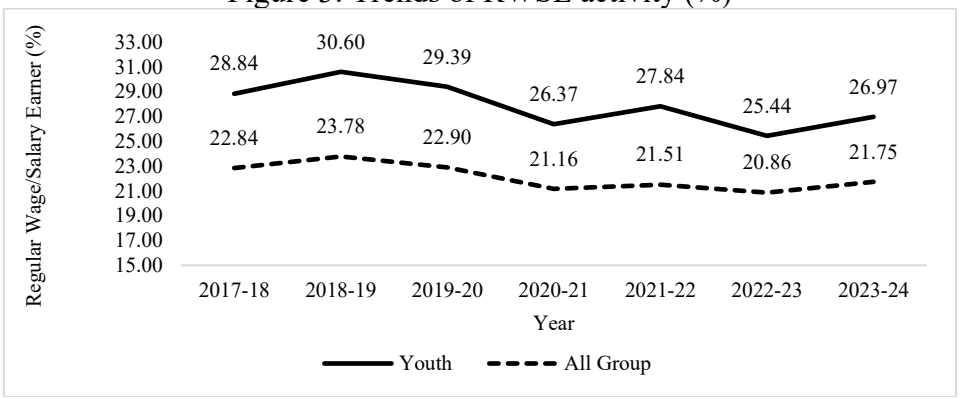
Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

Figure 2: Trends of unemployment rate (%)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data

Figure 3: Trends of RWSE activity (%)

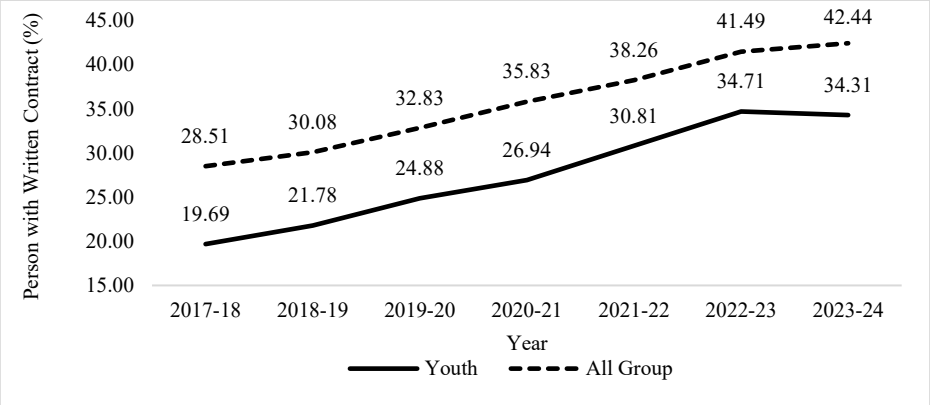


Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

Anyhow, despite their elevated participation, most youth in RWSE lack core contractual and social protections, namely written contracts, paid leave and social-security entitlements, and exhibit consistently lower coverage on these dimensions than the all age population across all survey rounds, indicating persistent informality within nominally regular employment. Positive improvements are evident; however, the incidence of written contracts among youth in RWSE increased from 19.69 per cent in 2017–18 to 34.31 per cent in 2023–24, corresponding to an average annual growth rate of 9.70 per cent, well above the 6.85 per cent growth rate for all

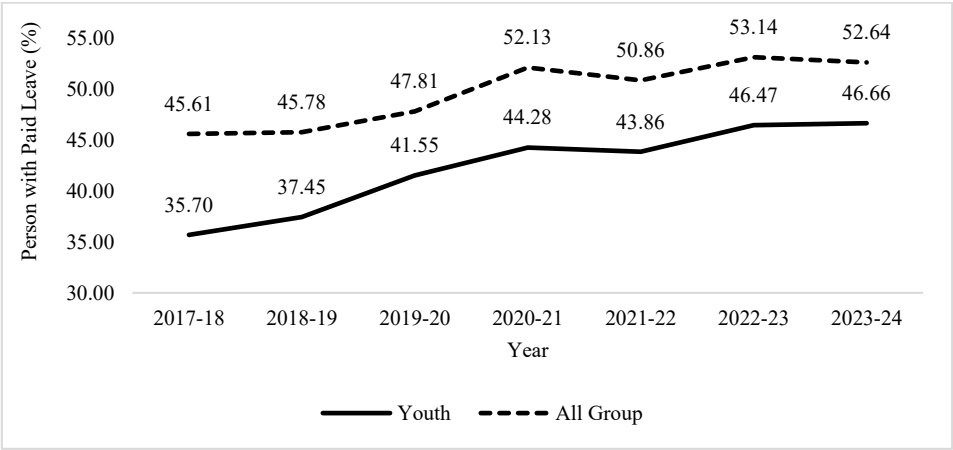
ages (Figure 4). Access to paid leave and social security among youth expanded at strong annual rates of 4.57 per cent and 4.58 per cent, respectively—more than double the growth recorded for the overall workforce engaged in RWSE (Figures 5–6). These patterns point to substantial improvements in the quality of youth employment within RWSE, while underscoring the remaining gaps in benefit coverage.

Figure 4: Person with written contract in RWSE activity (%)



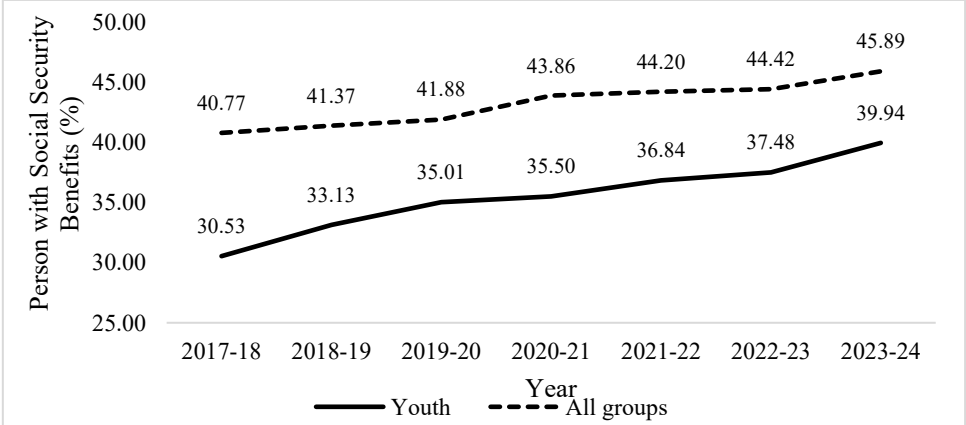
Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

Figure 5: Person with paid leave in RWSE activity (%)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

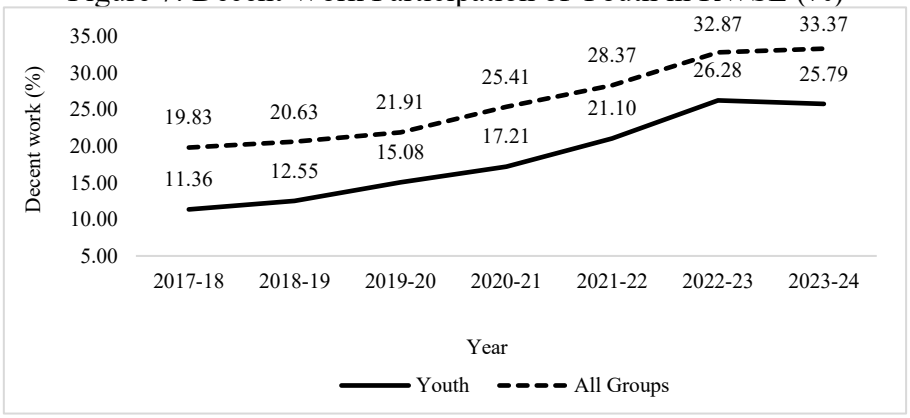
Figure 6: Person with social security benefit in RWSE activity (%)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

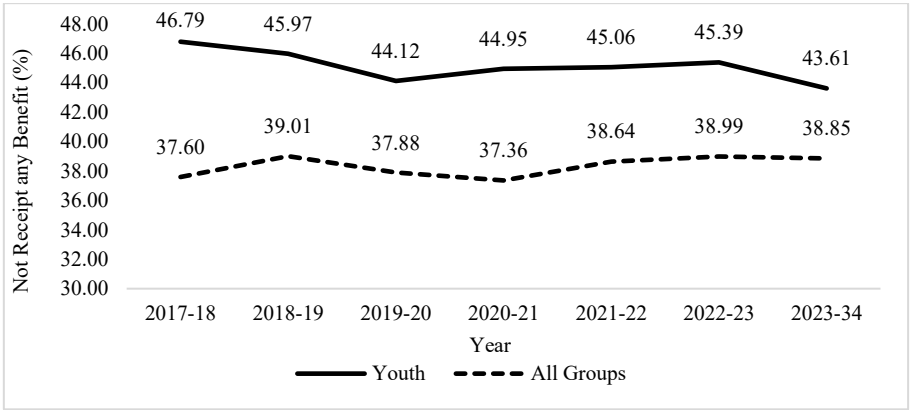
Between 2017–18 and 2023–24, the incidence of decent work among youth in RWSE rose from 11 per cent to 26 per cent (Figure 7), corresponding to an average annual growth rate of 14.63 per cent; substantially above the 9.06 per cent annual growth recorded for the overall working-age population. This divergence signals the relative formalisation of youth employment within RWSE and improved access to job protection and job quality for younger cohorts. Concurrently, the proportion of youth engaged in non-decent work fell marginally from 46.79 per cent to 43.61 per cent over the same interval, equivalent to an average annual change of −1.16 per cent (Figure 8). Although these patterns denote meaningful progress in youth employment quality, the continued prevalence of non-decent RWSE highlights persistent gaps in benefit coverage and worker protections that merit targeted policy attention.

Figure 7: Decent Work Participation of Youth in RWSE (%)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

Figure 8: Non-decent Work Participation of Youth in RWSE (%)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

4.1. Decent vs. Non-Decent Work: The Wage Gap and Inequality among Youth

Workers classified as experiencing decent work within RWSE show markedly superior employment outcomes compared with their counterparts in non-decent work. Specifically, decent workers are substantially more likely to benefit from core contractual and social

protections, including a written contract, access to paid leave and entitlement to social-security benefits, and they earn higher wages. Table 2 reports the median wage differentials between decent and non-decent workers across the wage distribution, documenting a persistent earnings premium associated with decent work. These findings underscore the distributional implications of job quality and the potential policy gains from extending contractual and social protections to currently non-decent RWSE positions.

Table 2: Median Monthly Wage/Salary Earnings and Wage Gap in RWSE-Youth (₹ /Nominal Price)

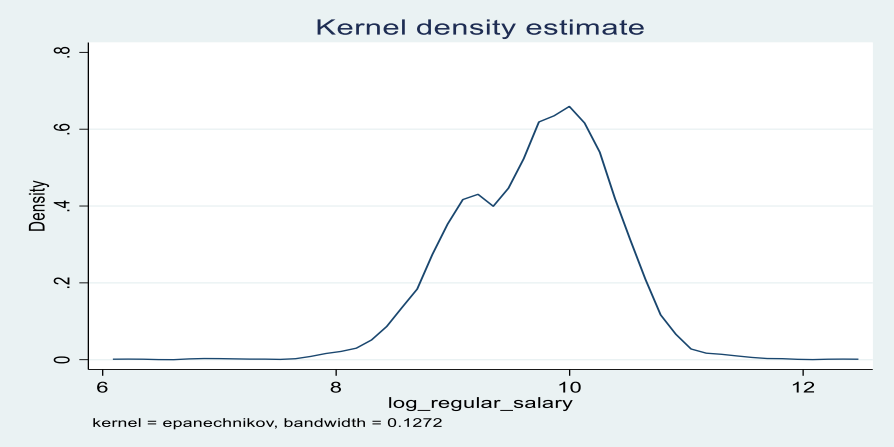
Percentile Group	2017-18			2023-24		
	Decent Worker (D)	Non-Decent Worker (ND)	Ratio D/ND	Decent Worker (D)	Non-Decent Worker (ND)	Ratio D/ND
10th Percentile	7000	3500	2.00	11500	5000	2.30
25th Percentile	10000	5000	2.00	15000	7800	1.92
50th Percentile	17000	7500	2.26	21000	10000	2.10
75th Percentile	25000	10000	2.50	33000	13000	2.53
95th Percentile	40000	15000	2.26	56000	19000	2.94

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24.

Distributional analysis of monthly wages indicates that workers classified as occupying decent positions earn substantially more than those in non-decent jobs across the wage distribution. The earnings gap between decent and non-decent employment is relatively narrow at the lower end of the wage distribution but increases monotonically toward the upper end. In 2023–24, the ratio of median wages (decent/non-decent) was 2.30 at the 10th percentile and rose to 2.94 at the 95th percentile. This upward-sloping wage ratio, together with temporal trends in the data, indicates a continued widening of these disparities, highlighting that the remuneration gap associated with job type has become increasingly pronounced.

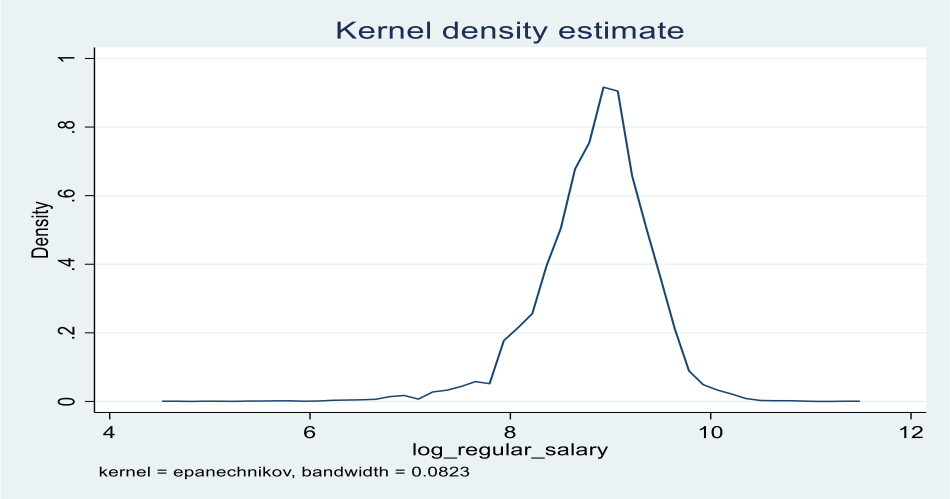
Figures 9–12 display kernel density estimates of the natural logarithm of monthly wages for workers classified as decent and non-decent. The kernel density estimation of decent and non-decent workers provides a clearer understanding of the wage distribution within the two groups. The density functions of these two groups are distinct from each other. The distribution of decent workers is wider, indicating that a larger proportion of workers in decent jobs earn higher wages. In contrast, the kernel density function for non-decent workers is narrower, suggesting that only a small proportion of them fall within the higher income brackets.

Figure 9: Kernel density function of log of regular salary/wage earner of youth engaged in decent work, 2017-18.



Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18.

Figure 10: Kernel density function of log of regular salary/wage earner of youth engaged in the non-decent work-2017-18

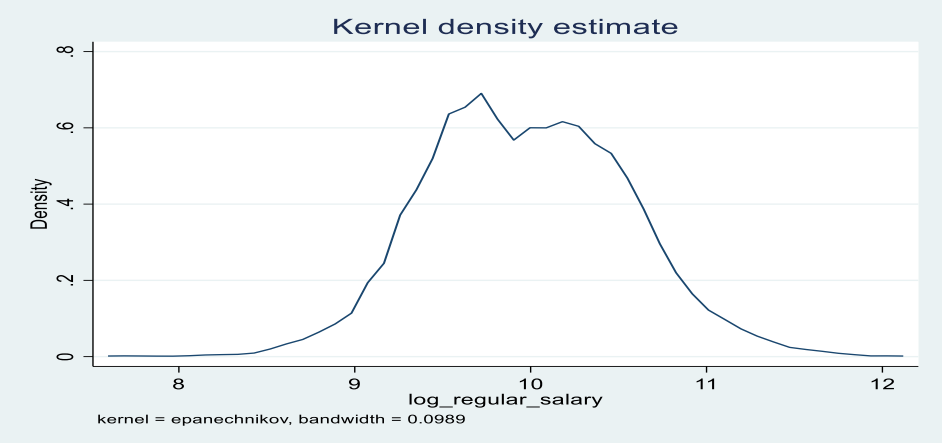


Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18.

Figures 11–12 show that in 2023–24, both decent and non-decent workers are increasingly represented in the higher wage brackets. This upward shift suggests that a larger segment of the workers is experiencing improvements in earnings. The evidence also indicates that, over time, even workers engaged in non-decent forms of employment have gained access to relatively better wages compared to earlier periods. However, unlike workers in decent employment, only a small proportion of non-decent workers situate themselves in the higher wage brackets. This implies that while a limited segment of such workers benefits from improved incomes, the vast majority remain concentrated in the lower wage segments. As a result, most non-decent workers continue to experience restricted monetary gains alongside the

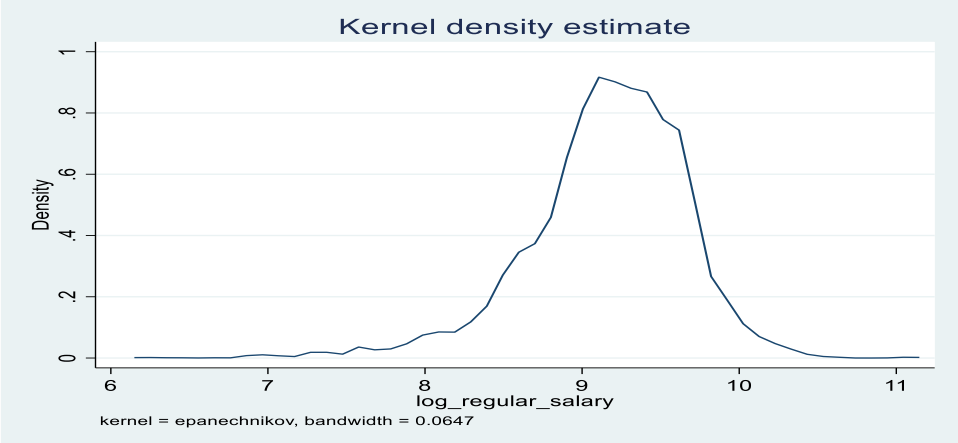
absence of essential benefits such as paid leave, written contracts, and social security, thereby underscoring their persistent economic vulnerability.

Figure 11: Kernel density function of log of regular salary/wage earner of youth engaged in decent work – 2023-24



Source: Authors' estimations based on unit-level data from NSS-PLFS, 2023-24.

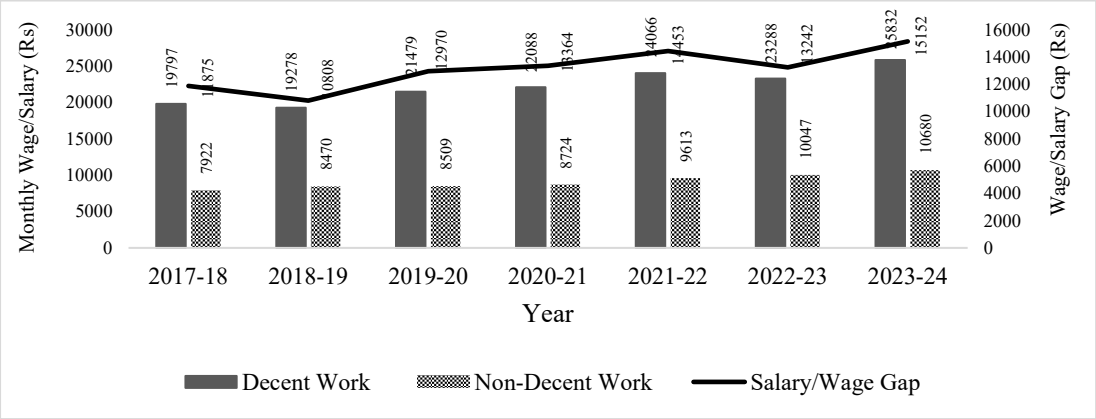
Figure 12: Kernel density function of log of regular salary/wage earner of youth engaged in the non-decent work-2023-24



Source: Authors' estimations based on unit-level data from NSS-PLFS, 2023-24.

Figure 13 documents a marked increase in the mean wage differential between workers classified as decent and non-decent. In 2017–18, mean monthly wages at nominal prices were ₹19,797 for decent workers and ₹7,922 for non-decent workers, yielding a gap of ₹11,875. By 2023–24, the mean wage gap had widened to ₹15152, signalling a substantial escalation in earnings divergence over the study period. A two-sample t-test confirms that the difference in mean wages between the two groups is statistically significant at the 1 per cent level. The persistence and expansion of this gap point to rising wage inequality within RWSE.

Figure 13: Wage/salary gap among the youth engaged in decent & non-decent work in RWSE activity (₹/Average wage/salary at nominal price)



Source: Authors' estimation from different rounds of NSS-PLFS unit-level data.

Employment outcomes are determined by a combination of factors, with education being a major determinant. Education and training constitute critical investments in human capital. According to human capital theory, higher levels of education are associated with greater returns in terms of productivity and earnings. The higher levels of education enhance a worker's knowledge, skills, and productivity, which in turn improve employment prospects and lead to higher wages. Table 3 shows that higher levels of education are associated with substantial increases in the monthly wages/salaries of both decent and non-decent workers engaged in regular wage/salary employment. However, it also reveals a concerning trend that the wage gap between decent and non-decent workers widens significantly as educational attainment rises.

In 2017–18, illiterate non-decent workers earned ₹3,969 less per month than their illiterate counterparts in decent employment (Table 3). Among workers with a graduate degree or higher, the disparity was even starker, with non-decent workers earning ₹13,819 less. By 2023–24, the wage gap had widened further: illiterate non-decent workers earned ₹4222 less, while the gap at the graduate-and-above level escalated to ₹19897. With the exception of the secondary education level, wage differentials between the two groups expanded consistently with rising levels of education. These findings underscore a deeper inequality in labour market outcomes, even among the most highly educated.

The degree of wage inequality in both decent and non-decent forms of employment varies significantly across different educational levels. Higher levels of education, with the exception of illiterate workers, have demonstrated an increase in inequality in wage earning within the decent work category during 2023–24. As educational attainment rises, the range of available occupations expands, leading to greater diversity in wage levels. Furthermore, given that decent

work is primarily found in the formal sector, institutional characteristics such as hierarchical structures, promotion pathways, and varied career trajectories further exacerbate wage disparities among the more educated workforce. A similar pattern is observed among non-decent workers.

Table 3: Education wise average monthly wage/salary earnings & wage inequality of youth engaged in RWSE (₹ /Nominal Price)[7]

Year	Education Level	Work Types & Inequality in Wages			
		Decent Work	Non-Decent Work	Gini Index Decent Work	Gini Index Non-Decent Work
2017-18	Illiterate	11473	7504	0.34	0.28
	Education up to Secondary	12828	7483	0.32	0.26
	Higher Secondary & Diploma/Certificate Course	14994	8212	0.33	0.25
	Graduation & above	23415	9596	0.34	0.31
2023-24	Illiterate	13134	8912	0.31	0.24
	Education up to Secondary	13574	10463	0.20	0.23
	Higher Secondary & Diploma/Certificate Course	18192	11276	0.23	0.24
	Graduation & above	30911	11014	0.29	0.30

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24.

In 2023–24, wage inequality within non-decent work was consistently higher across all educational levels compared to decent work, with the exception of illiterate workers. This outcome may reflect a greater degree of informalisation and the diverse wage setting mechanisms that typically characterise non-decent forms of employment. Relative to 2017–18, wage inequality declined in 2023–24 across all educational levels for both decent and non-decent workers, indicating a relative narrowing of the wage inequalities among the workers. Nonetheless, this decline signals progress towards wage convergence; however, it does not necessarily indicate improvements in job quality or the eradication of underlying structural inequalities within the labour market.

The International Standard Classification of Occupations (ISCO) 2008, defines occupational skill levels primarily in terms of the formal education typically required for job incumbents, categorising them into four ordinal skill levels. The National Classification of Occupations (NCO) of India adopts this framework. At the one-digit level of the National Classification of Occupations (NCO), all occupations are grouped into nine major categories. They are legislators, senior officials and managers; professionals; associate professionals; clerks; service workers and shop and market sales workers; skilled agricultural and fishery workers; craft and

[7] The wage differentials between decent and non-decent workers across all levels of education are statistically significant at the 1 per cent level (t-test).

related trades workers; plant and machine operators and assemblers; and elementary occupations. However, the NCO deliberately avoids assigning a specific skill level to the category of legislators, senior officials, and managers, citing the substantial heterogeneity of tasks and competencies within this group, which precludes a meaningful correspondence with ISCO's four discrete skill levels. For the remaining eight categories, the NCO provides a map to ISCO skill levels: Professionals and technical/associate professionals are placed at skill level 4 and skill level 3, respectively; clerks, service and shop and market sales workers, skilled agricultural and fishery workers, craft and related trades workers, and plant and machine operators and assemblers are predominantly located at skill level 2; and elementary occupations are classified at skill level 1.

Table 4 presents the distribution of workers across educational categories and skill levels for 2017–18 and 2023–24, distinguishing between decent and non-decent employment. As anticipated, illiterate workers remain overwhelmingly concentrated in the lower-skill segments across both forms of employment. The majority of workers with secondary and higher secondary education remain concentrated in skill level 2. For individuals with higher secondary education & diplomas, the share of decent workers in skill level 4 increased from 13.97 per cent in 2017–18 to 18.33 per cent in 2023–24, reflecting improved access to higher-skill occupations. In contrast, the distribution of non-decent workers within the same skill level remained largely unchanged. At the same time, for both decent and non-decent workers holding higher secondary or diploma qualifications, the share in skill level-3 declined between 2017–18 and 2023–24, with much of this shift absorbed into skill level-2 jobs.

The most significant transformation is evident among graduates and above. The share of decent workers at skill level-4 rose sharply from 34.46 per cent in 2017–18 to 55.14 per cent in 2023–24, illustrating a strengthening returns-to-education effect. Simultaneously, the share of graduates among non-decent workers at skill level 4 also increased, from 26.37 per cent in 2017–18 to 35.10 per cent in 2023–24, indicating that although higher education provides greater access to high-skill jobs, it does not guarantee decent work. This paradox advocates that while education plays a critical role in improving access to higher skill levels and decent work, it is not a sufficient condition, as many graduates continue to face risks of underemployment and informality. This may be attributed to both demand-side and supply-side constraints in the labour market. On the demand side, challenges include limited labour demand in certain formal-sector industries and a mismatch between employers' skill requirements and the available

workforce. On the supply side, factors such as inadequate skill specialisation among highly educated individuals and rigid labour market regulations continue to restrict worker mobility.

Table 4: Distribution of RWSE by education and skill levels among youth (%)

Year	Education	Skill Level							
		Decent Worker				Non-Decent Worker			
		1	2	3	4	1	2	3	4
2017-18	Illiterate	67.24	30.82	1.75	0.19	45.32	53.06	1.05	0.57
	Education up to Secondary	19.17	64.13	13.70	3.00	18.77	76.96	2.65	1.63
	Higher Secondary & Diploma/Certificate Course	4.51	51.15	30.36	13.97	10.88	71.37	10.21	7.54
	Graduation & above	1.26	29.73	34.56	34.46	3.47	45.92	24.25	26.37
2023-24	Illiterate	66.68	31.58	0.33	1.42	51.19	48.12	0.33	0.36
	Education up to Secondary	27.20	61.06	8.40	3.34	24.24	71.75	2.30	1.71
	Higher Secondary & Diploma/Certificate Course	8.22	55.11	18.34	18.33	10.98	75.25	6.42	7.35
	Graduation & above	0.84	30.93	13.08	55.14	4.20	52.41	8.29	35.10

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24.

Table 5: NCO wise average monthly wage/salary earnings & wage inequality of youth engaged in RWSE activities (₹ /Nominal Price)[8]

Year	Skill Level	Decent Worker	Non-Decent Worker	Gini Index Decent Worker	Gini Index Non-decent Worker	Wage Gap
2017-18	1	12289	6918	0.33	0.27	5371
	2	16888	7975	0.31	0.26	8913
	3	19631	7711	0.37	0.32	11920
	4	25585	9674	0.28	0.34	15911
2023-24	1	12903	9365	0.20	0.23	3538
	2	19671	10915	0.25	0.23	8756
	3	22329	10671	0.26	0.28	11658
	4	35991	9468	0.27	0.38	26523

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24

Table 5 shows that as the skill level increases, the wage gap between the decent and the non-decent increases. Compared to 2017–18, the wage gap at higher skill levels widened significantly in 2023–24. During 2017-18, the wage gap between workers in decent and non-decent employment at skill level 4 was ₹ 15911, which increased to ₹ 26523 in 2023-24. In contrast, at all other skill levels, the wage gap between decent and non-decent workers declined over the same period. These findings are somewhat counterintuitive and suggest the presence of labour market distortions. Several factors may explain this anomaly. Structural mismatches between educational qualifications and job requirements, particularly in the informal sector or in underdeveloped labour markets, may result in educated workers being employed in low-

[8] The wage differentials between decent and non-decent workers across all levels of education are statistically significant at the 1 per cent level (t-test).

productivity or low-paying jobs. Additionally, an oversupply of degree holders in certain segments of the labour market may exert downward pressure on wages due to surplus supplies.

In 2023–24, wage inequality within decent jobs was highest at skill level 4, with a Gini index of 0.27 indicating substantial disparities among highly skilled workers even in formalised employment. Wage inequalities progressively decrease from skill level 4 to level 1, suggesting that lower-skilled jobs tend to have more uniform compensation, possibly because wages in these roles are already substantially lower. Compared to 2017–18, wage inequality in decent work declined across all skill levels by 2023–24, reflecting improvements in wage distribution over time. In contrast, for non-decent work, wage inequality decreased in all skill levels except skill level-4, implying persistent disparities among the high-skilled informal workers. In 2023–24, wage inequality in non-decent work was higher than in decent work across all skill levels except skill level-2, highlighting the vulnerability of informal workers to wage dispersion.

4.2. Wage Penalty for Youth Engaged in Non-Decent Work

The above discussion underscores the existence of a substantial wage disparity between workers engaged in decent and non-decent forms of employment. Importantly, this disparity persists even when individuals from both groups possess comparable levels of education and are employed in the same occupational categories, suggesting that the quality of employment itself is a critical determinant of earnings. To examine this relationship more rigorously, Table 6 reports the regression estimates obtained from OLS as well as CQRM without sample selectivity bias. The methodological section of this study systematically discusses the details of the dependent, independent, and control variables of the regression model.

The OLS regression results reveal that in both 2017–18 and 2023–24, the coefficient for non-decent workers is negative, indicating a persistent wage disadvantage relative to their decent counterparts. Holding all other factors constant, non-decent workers earned, on average, approximately 77 per cent less than decent workers in 2017–18 and about 70 per cent less in 2023–24. Although the magnitude of this wage penalty declined slightly over time, the findings underscore that non-decent employment remains strongly associated with a substantial earnings gap. In 2023–24, individuals without vocational education earned about 5 per cent less salary compared to their counterparts with vocational training. Consistent with the expected returns-to-education effect, regular employees with higher levels of education received significantly higher wages than illiterate workers. Belonging to the SC/ST category was associated with a clear wage disadvantage. Holding other factors constant, SC/ST workers

earned about 4 per cent less than their non-SC/ST counterparts in 2017–18, and the gap widened to around 8 per cent in 2023–24. Evidence from earlier studies also highlights that, across sectors, SC/ST workers face persistent discrimination, earning lower wages than other social groups despite having similar qualifications (Madheswaran & Singhari, 2016). Similarly, the regression results indicate a pronounced gender gap, with women earning significantly lower wages than men. The Indian labour market exhibits substantial heterogeneity in occupational structures and skill levels, as defined by the NCO discussed earlier in this study. Empirical evidence highlights a steep wage gradient across the skill level. The regression results indicate that earnings from jobs in skill levels 1, 2, and 3 are significantly lower compared to those in skill level 4.

The simple OLS regression model provides an estimate of the average wage penalty associated with non-decent employment among RWSE. However, wage outcomes often vary substantially across different points of the wage distribution, implying that workers at the lower end may face a different magnitude of wage penalty compared to those at the upper end. To address this heterogeneity, quantile regression is employed, as it enables the estimation of wage penalties for non-decent workers at different points in the distribution. Specifically, the CQRM is applied, segmenting the wage distribution into five representative percentiles: the 10^{th}, 25^{th}, 50^{th} (median), 75^{th}, and 95^{th}. In 2017–18, results indicate that at the 10^{th} percentile, non-decent workers earned 68 per cent less than their decent counterparts. Moving from the lower tail to the upper tail of the distribution, the wage penalty increased considerably. By 2023–24, the penalty at the lowest quintile rose slightly to 73 per cent, whereas at the highest quintile it declined to 71 per cent. All these estimates are statistically significant at the 1 per cent level, highlighting a persistent and significant wage disadvantage for non-decent workers, with notable variations across the distribution.

Across all quintile groups in both 2017–18 and 2023–24, female employees consistently earned lower wages than their male counterparts. In 2023–24, at the 10^{th} percentile, female workers earned approximately 41 per cent less than male workers. At the 25^{th}, 50^{th}, 75^{th}, and 95^{th} percentiles, women earned 35 per cent, 29 per cent, 21 per cent, and 13 per cent less than men, respectively, with all estimates statistically significant at the 1 per cent level. This declining trend indicates that the gender wage gap is more pronounced among lower-wage earners. One possible explanation is that women in the lower wage percentile are concentrated in lower-skilled types of employment. On the other hand, women in the higher wage quintiles are more likely to work in skilled and structured jobs, which helps close the wage gap. In both years,

urban workers consistently earned higher wages than their rural counterparts across all quintiles, underscoring the persistent and deep-rooted structural inequalities that characterise India's labour market.

Vocational and technical training play a minor role in enhancing wages. Across wage quintiles during 2023–24, individuals without vocational training earned approximately only 3 per cent to 5 per cent less than those with vocational training. A possible explanation is that employers may tend to offer higher wages to workers who require minimal training and can immediately carry out technical tasks efficiently. In line with this, the returns to advanced vocational training are higher in the upper end of the wage distribution and, in fact, exceed those from general education (Andersson et. al., 2014).

From an economic perspective, the relationship between education and earnings is generally positive, in line with human capital theory, which posits that higher levels of education enhance productivity and, consequently, increase wages. Using illiterate workers as the reference group, the quantile regression results for 2023–24 reveal varying returns to education across the wage distribution. At the 10^{th} percentile, individuals with secondary education earned approximately 43 per cent more than illiterate workers. However, the returns to secondary education diminish at higher percentiles. Individuals with graduate-level education and above exhibit a similar pattern. At the 10th and 95th percentiles, they earned 62 per cent and 25 per cent more, respectively, than illiterate workers. These findings deviate from the standard Mincer (1958) model, which proposes a log-linear relationship between years of schooling and the logarithm of earnings, implying that each additional year of schooling yields a roughly constant percentage increase in wages (Heckman et. al., 2005). In contrast, this study shows that in India, this relationship does not hold, particularly at the higher percentiles of the wage distribution

During 2023–24, at the median of the wage distribution, skill level-1 workers earned approximately 23 per cent less in salaries compared to those in skill level-4. However, at the 75^{th} and 95^{th} percentiles of the wage distribution, this earnings disadvantage widened to 28 per cent and 31 per cent, respectively, relative to their corresponding reference categories. Similarly, for skill level 2, the wage difference increased significantly as individuals moved from the lower wage quintile to the upper wage quintile, indicating a steady rise in wage disparities compared to their reference group. This pattern suggests that high-ranking professional occupations experience an amplification effect in earnings at the upper end of the

wage distribution, possibly due to factors such as higher skill premiums and a scarcity of specialised expertise at the senior level. For skill level 3, earnings at the lower end of the wage distribution are about 10 per cent lower than those in skill level 4. However, as we move toward the upper tail of the wage distribution, their wage disadvantage increased.

Table 7 presents the regression estimates for 2017–18 and 2023–24, accounting for potential sample selection bias through the inclusion of the IMR as an additional regressor. While the coefficients obtained from models with and without correction for sample selection bias do not differ substantially, the estimates from the selection-corrected model are statistically more robust and reliable, thereby reinforcing the credibility of the results compared to the standard quantile regression.

The result of table 7 is more robust than table 6. In both 2017–18 and 2023–24, most of the coefficients of the IMR are positive and statistically significant at the 1 per cent level across the percentiles of the wage distribution. This provides strong evidence of sample selection bias in the regression model, indicating that the observed wage outcomes are systematically influenced by the non-random selection of individuals into employment. The regression results for 2017–18 show that non-decent workers faced a more severe wage disadvantage at the upper end of the distribution compared to the lower end. In 2023–24, although the wage penalty for non-decent workers declined relative to 2017–18, significant disparities remained. For instance, at the median percentile of the wage distribution in 2023–24, non-decent workers earned approximately 59 per cent less than their decent counterparts, compared to 76 per cent in 2017–18. At the 95^{th} percentile, the wage gap in 2023–24 widened further, though it remained smaller than the corresponding figure for 2017–18. This indicates that while disparities persisted at the upper end of the wage distribution, they declined over time. All these differences are statistically significant at the 1 per cent level, underscoring the robustness of the results and the persistent disadvantage faced by non-decent workers.

The negative and statistically significant coefficient on the female variable across all quantiles confirms that female workers consistently earn less than their male counterparts, with the gender wage gap being most pronounced at the lower end of the wage distribution. These findings suggest that, although gender-based wage inequalities remain a structural feature of the labour market, they have declined over time.

Table 6: OLS & conditional quintile regression without sample selectivity biased

Variables	2017-18						2023-24					
	OLS Regression	**10th P**	**25th P**	**50th P**	**75th P**	**95th P**	**OLS Regression**	**10th P**	**25th P**	**50th P**	**75th P**	**95th P**
Non-decent worker	-0.768*** (0.017)	-0.681*** (0.030)	-0.634*** (0.025)	-0.759*** (0.020)	-0.851*** (0.017)	-0.850*** (0.033)	-0.700*** (0.013)	-0.727*** (0.025)	-0.607*** (0.016)	-0.598*** (0.014)	**-0.605*** (0.016)**	-0.711*** (0.021)
Gender	-0.361*** (0.018)	-0.470*** (0.031)	-0.405*** (0.026)	-0.353*** (0.021)	-0.272*** (0.017)	-0.188*** (0.034)	-0.300*** (0.013)	-0.405*** (0.026)	-0.346*** (0.017)	-0.285*** (0.014)	-0.210*** (0.017)	-0.130*** (0.022)
Sector	0.0872*** (0.013)	0.0527** (0.023)	0.0760*** (0.020)	0.0735*** (0.016)	0.101*** (0.013)	0.0670** (0.026)	0.112*** (0.011)	0.154*** (0.021)	0.112*** (0.014)	0.0880*** (0.012)	0.094*** (0.014)	0.0870*** (0.018)
SC/ST	-0.0450*** (0.015)	-0.0527** (0.025)	-0.0477** (0.021)	-0.0367** (0.017)	-0.0566*** (0.014)	-0.099*** (0.028)	-0.0898*** (0.012)	-0.0761*** (0.023)	-0.0896*** (0.015)	-0.0880*** (0.013)	-0.0940*** (0.015)	-0.0936*** (0.019)
No-Vocational Training	0.0318* (0.017)	0.0527* (0.029)	0.0477** (0.024)	0.0288 (0.019)	0.0165 (0.016)	0.000 (0.032)	-0.0520*** (0.011)	-0.0354* (0.021)	-0.0556*** (0.013)	-0.0529*** (0.011)	-0.0588*** (0.013)	-0.0423** (0.017)
Education up to Secondary	0.0734** (0.037)	0.0408 (0.066)	0.0953* (0.055)	0.102** (0.044)	0.130*** (0.037)	0.0348 (0.074)	0.166*** (0.038)	0.428*** (0.074)	0.223*** (0.048)	0.105** (0.041)	0.102** (0.048)	0.105* (0.063)
Higher Secondary & Diploma/Certificate	0.159*** (0.039)	0.0935 (0.069)	0.182*** (0.057)	0.199*** (0.046)	0.195*** (0.039)	0.099 (0.077)	0.169*** (0.039)	0.428*** (0.076)	0.244*** (0.049)	0.107** (0.042)	0.137*** (0.049)	0.148** (0.064)
Graduation & above	0.332*** (0.040)	0.276*** (0.071)	0.366*** (0.059)	0.345*** (0.047)	0.345*** (0.040)	0.199** (0.079)	0.357*** (0.040)	0.618*** (0.078)	0.391*** (0.050)	0.289*** (0.043)	0.290*** (0.050)	0.248*** (0.066)
Skill level-1	-0.135*** (0.028)	-0.0532 (0.049)	-0.164*** (0.041)	-0.143*** (0.033)	-0.150*** (0.028)	-0.213*** (0.055)	-0.144*** (0.024)	0.000 (0.046)	-0.0927*** (0.030)	-0.226*** (0.025)	-0.284*** (0.030)	-0.311*** (0.039)
Skill level-2	-0.0922*** (0.025)	0.000 (0.043)	-0.0981*** (0.036)	-0.106*** (0.029)	-0.158*** (0.025)	-0.264*** (0.048)	-0.150*** (0.017)	0.000 (0.034)	-0.114*** (0.022)	-0.249*** (0.019)	-0.299*** (0.022)	-0.417*** (0.028)
Skill level-3	-0.161*** (0.031)	-0.182 (0.054)	-0.146*** (0.045)	-0.143*** (0.036)	-0.162*** (0.030)	-0.385*** (0.060)	-0.276*** (0.022)	-0.104** (0.043)	-0.217*** (0.028)	-0.388*** (0.024)	-0.429*** (0.028)	-0.569*** (0.037)
Constant	9.554*** (0.050)	8.829*** (0.087)	9.126*** (0.072)	9.587*** (0.058)	9.972*** (0.049)	10.63*** (0.097)	9.83*** (0.044)	8.844*** (0.086)	9.407*** (0.055)	9.951*** (0.047)	10.29*** (0.055)	10.84*** (0.072)
Observations	7,173	-	-	-	-	-	9,321	-	-	-	-	-
R-squared/Pseudo R^2	0.352	0.131	0.136	0.177	0.276	0.327	0.432	0.200	0.206	0.238	0.310	0.357

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24

Note: ***, **, * denote significance at the 1, 5 and 10 per cent, respectively. The figures in parentheses are standard errors.

Table 7: Conditional quintile regression with sample selectivity biased

	2017-18					2023-24				
Variables	**10th P**	**25th P**	**50th P**	**75th P**	**95th P**	**10th P**	**25th P**	**50th P**	**75th P**	**95th P**
Non-decent worker	-0.690*** (-0.031)	-0.637*** (0.024)	-0.762*** (0.019)	-0.854*** (0.013)	-0.862*** (0.033)	**-0.713*** (0.022)**	-0.621*** (0.016)	-0.594*** (0.014)	-0.615*** (0.017)	-0.709*** (0.023)
Gender	-0.392*** (0.060)	-0.357*** (0.045)	-0.254*** (0.037)	-0.186*** (0.026)	-0.106* (0.063)	-0.424*** (0.023)	-0.346*** (0.017)	-0.290*** (0.015)	-0.215*** (0.017)	-0.132*** (0.024)
Sector	0.0367 (0.027)	0.0537*** (0.021)	0.0704*** (0.017)	0.0769*** (0.012)	0.0403 (0.029)	0.299*** (0.035)	0.242*** (0.025)	0.165*** (-0.022)	0.143*** (0.026)	0.101*** (0.036)
SC/ST	0.162 (0.138)	0.102 (0.104)	0.224*** (0.085)	0.162*** (0.059)	0.192 (0.145)	0.0525 (0.036)	0.0441* (0.026)	-0.0114 (0.023)	-0.0487* (0.026)	-0.0777** (0.036)
No-Vocational Training	-0.0854 (0.093)	-0.0461 (0.071)	-0.147** (0.057)	-0.129*** (0.040)	-0.203** (0.098)	-0.266*** (0.048)	-0.257*** (0.035)	-0.168*** (0.031)	-0.124*** (0.036)	0.0663 (0.049)
Education up to Secondary	0.560* (0.326)	0.447* (0.247)	0.705*** (0.200)	0.644*** (0.139)	0.713** (0.343)	1.139*** (0.166)	0.928*** (0.120)	0.519*** (0.105)	0.359*** (0.124)	0.186 (0.170)
Higher Secondary & Diploma/Certificate	1.367* (0.787)	1.074* (0.596)	1.705*** (0.484)	1.472*** (0.336)	1.737** (0.827)	2.016*** (0.348)	1.810*** (0.250)	1.021*** (0.221)	0.687*** (0.259)	0.325 (0.357)
Graduation & above	2.099* (1.116)	1.630* (0.845)	2.504*** (0.687)	2.154*** (0.477)	2.536** (1.174)	2.830*** (0.475)	2.538*** (0.342)	1.539*** (0.301)	1.045*** (0.353)	0.501 (0.487)
Skill level-1	-0.0856 (0.056)	-0.186*** (0.042)	-0.159*** (0.034)	-0.183*** (0.024)	-0.246*** (0.058)	0.237*** (0.057)	0.0735* (0.041)	-0.125*** (0.036)	-0.208*** (0.042)	-0.297*** (0.059)
Skill level-2	-0.306 (0.204)	-0.344** (0.154)	-0.485*** (0.126)	-0.472*** (0.087)	-0.672*** (0.215)	-0.458*** (0.107)	-0.597*** (0.077)	-0.532*** (0.068)	-0.450*** (0.080)	-0.469*** (0.110)
Skill level-3	-0.512** (0.235)	-0.406** (0.178)	-0.566*** (0.144)	-0.521*** (0.100)	-0.844*** (0.247)	-0.159*** (0.042)	-0.308*** (0.030)	-0.432*** (0.027)	-0.452*** (0.031)	-0.575*** (0.043)
IMR	1.329 (0.829)	0.951 (0.627)	1.626*** (0.510)	1.342*** (0.354)	1.719** (0.871)	1.477*** (0.315)	1.442*** (0.226)	0.830*** (0.199)	0.506** (0.234)	0.164 (0.322)
Constant	6.169*** (1.641)	7.271*** (1.242)	6.375*** (1.010)	7.311*** (0.701)	7.224*** (1.726)	5.960*** (0.614)	6.629*** (0.442)	8.342*** (0.389)	9.298*** (0.457)	10.52*** (0.630)
Pseudo R^2	0.131	0.136	0.178	0.277	0.328	0.206	0.209	0.239	0.311	0.357

Source: Authors' estimations based on unit-level data from NSS-PLFS, 2017–18 and 2023–24.

Note: ***, **, * denote significance at the 1, 5 and 10 per cent, respectively. The figures in parentheses are standard errors.

The study find that vocational and technical training significantly improves wage outcomes across the earnings distribution. In 2023–24, individuals without vocational training earned approximately 26 per cent less than those with such training at the lowest percentile. However, relative to the reference category, the wage differences declined to only 6 per cent at the highest percentile.

Education level has a positive impact on wages, and the return on education increases with higher levels of educational attainment. In both 2017–18 and 2023–24, across all education levels, returns were highest at the lowest percentiles of the wage distribution. This may be because individuals in the top percentiles of each education category already earn relatively high salaries, so additional education has a limited impact on further increasing their wages. In 2023–24, skill level-1 workers earned unexpectedly higher wages than skill level-4 workers at the 10^{th} and 25^{th} percentiles of the wage distribution. However, this advantage reversed sharply at the upper tail, with earnings gaps widening to 21 per cent at the 75^{th} percentile and 30 per cent at the 95^{th} percentile. For skill level 2, wage disparities increased sharply from the 10^{th} to the 25^{th} percentile and then declined gradually thereafter. By contrast, skill level-3 workers faced a consistent disadvantage: their wages were 16 per cent lower than skill level-4 workers at the bottom of the distribution, and the gap intensified to 58 per cent at the 95^{th} percentile.

5. Conclusion

This study investigates the wage gap between decent and non-decent workers in India, with a particular focus on youth employment. Over the study period, youth workforce participation increased notably, driven by a decline in unemployment. Although the share of young people in RWSE declined somewhat between 2017–18 and 2023–24, it remained higher than overall RWSE. Key indicators of decent work such as written contracts, paid leave, and social security coverage have consistently been lowered for youth compared to the broader workforce. Nevertheless, access to these protections has significantly improved over time, indicating the gradual formalisation of youth employment. These trends suggest an overall improvement in job quality among young workers, shaped by policy initiatives and structural shifts that expand opportunities for decent work activity.

Educational attainment is positively associated with wage outcomes; however, the wage differential between decent and non-decent workers also tends to increase with higher levels of education. Similarly, skill level emerges as a critical determinant of wage disparities. At lower skill levels, the wage gap between decent and non-decent workers is relatively narrow,

but it broadens considerably as skill levels rise, indicating that non-decent workers are disproportionately disadvantaged in higher-skill occupations.

A comprehensive analysis of the wage distribution indicates that the gap between decent and non-decent workers follows an inverted U-shape. The wage penalty for non-decent workers is highest in the lowest wage quintile, decreases across the middle wage quintiles, and rises again significantly at the highest wage quintile, underscoring persistent structural inequalities in the labour market. However, the wage penalty for non-decent workers has declined over time, particularly at higher wage percentiles.

Overall, these findings illuminate the dual dynamics of India's labour market. On one hand, there is evidence of progressive formalisation and improved employment protections for youth, reflecting positive developments in job quality. On the other hand, significant and persistent wage disparities remain between decent and non-decent workers, particularly among highly educated and higher-skilled employees. The analysis underscores the need for targeted policy interventions to reduce these inequalities and ensure that gains in youth employment translate into equitable and secure labour market outcomes across all wage segments.

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