Dynamics of Income Inequality and Employment Characteristics under Different Growth Regimes: Insights from Household Level Survey Data in India

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This study explores the distributional issues of growth by taking labour market characteristics into account with micro level information from employment and unemployment survey in India. The study analyses how inequality has changed with employment characteristics over the new growth regimes in India that started in the early 1980s by using Gini index and decomposing it into 'within' group and 'between' group inequality. While within group inequality declined, the between group inequality increased markedly during the 1990s and became stagnant thereafter in the rural economy. The incidence of inequality was higher in the urban economy as compared to the countryside. The within group inequality increased at a higher rate among regular wage earners than the self-employed group during the initial decade of reforms. To locate the possible factors for inequality we have estimated conditional earnings at different quantiles. The estimated results suggest that higher the level of education higher is the wage earned by the workers. As returns to education at a particular education level were higher at the upper quantiles, the wage distribution became more unequal because of education and the effect was escalating over time. Earnings inequality between different groups of workers even at the same level of education increased over time during the post-reforms period.

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1. Introduction

The growth effect transmits to inequality and poverty mainly through labour market dynamics. In effect, poverty persists in low income countries primarily because of high unemployment, low productivity, and income inequality (Guitierrez et al 2007). There is strong evidence suggesting that, in low or lower middle income countries, a very small part of the workforce is absorbed in the high productive formal sector and mostly of them come

from the upper class in social strata with high skill, but a significant share of the workers are vulnerable and forced to accept less productive informal jobs. The dualistic structure of the labour market in this shape is highly significant in analysing inequality in a country like India. The gap in income between those who are at the top stratum and at the bottom will increase the vulnerability of the later, because more inequitable system provides better and more opportunities to the rich enjoying hegemony in different forms in the society over the poor.

Against this backdrop, the objective of this study is to explore the distributional issues of growth since the early 1980s by taking labour market characteristics into account with micro level information from employment and unemployment survey in India. The employability of a person is affected highly by the social and demographic characteristics of individuals, such as social status, family background, gender, along with the level of schooling. We have examined how the household specific factors are associated with wage distribution and consumption distribution by applying quantile regression model. The study covers the period from 1983 to 2012.

The sources of inequality in less developed countries are different from those in developed countries both in subjective and objective norms. But, human capital, particularly education, is very much crucial in explaining inequality through labour market dynamics in every economy[1]. It is well documented that better-educated persons are able to earn higher wages, experience less unemployment, and work in more high-status occupations than their less-educated counterparts (Cohn and Addison 1997). The returns to education increase with skill-biased technical change demanding more for skilled workers. As the relationship between education and earnings is nonlinear, educational expansion can increase earnings inequality even if the educational distribution is unchanged (Goldberg and Pavcnik 2007). The seminal work of Neal and Johnson (1996) showed that controlling for educational achievement reduced the wage gap between blacks and whites.

The study observes positive effect of education on within-groups inequality. However, the impact differs significantly across different types of workers with different education levels. The differences across quantiles are substantially higher for workers with graduate and above than for less educated workers. Using data from the last three decades,

[1] The issue relating to human capital and growth was started to stimulate in the late 1950s by the belief that increasing human capital could explain much of the productivity growth, leaving little contribution for technological change (Becker, 1964; Griliches, 1977).

we analyse changes in inequality between and within groups. This study, in estimating the effect of education and types of employment on inequality, may be helpful to reconcile the various findings in the literature, and provides a useful framework for generating new hypotheses and insights about the connection between employment characteristics and earnings inequality.

The study is organised into seven sections. After some introductory remarks in section 1, section 2 discusses the econometric model used in this study. We have used survey data to analyse inequality. Section 3 describes, in short, the data. Section 4 examines the changes in occupational status and employment characteristics in terms of education. Section 5 analyses the changing pattern of income inequality in terms of per capita consumption expenditure and earnings inequality in terms of weekly wages earned by the workers. The Gini inequality index is decomposed into 'within' group and 'between' group components. Section 6 interprets in detail the estimated results of quantile regression equation. Section 7 summarises and concludes.

2. The econometric model

Quantile regression model is used to study the disproportional effect of education and employment characteristics on wages in different percentiles and thus, trends in income inequality in India over different survey rounds on household consumer expenditure since the early 1980s. While the ordinary least-squares (OLS) estimates measure the effects of predictors on the response variable upon the mean of the conditional distribution of the response variable, quantile regression measures the effects of the predictors at different points of the distribution. Differences in quantile response can be used to measure inequality within groups. In this study, the types of employment and education level are taken as the major predictors of the response variable earnings. We consider levels of education below primary, primary, middle, secondary, and graduate and above for workers of different types by generating dummy variables at each level of education. We have not used least-squares regression because it fails to detect the impact of employment characteristics and education on the shape of the earnings distribution. Quantile regression, on the other hand, is helpful in studying the conditional quantiles of earnings (y) depending on types of employment and levels of education (x) of the distribution.

For a random variable *Y* with probability distribution function $F(y) = P(Y \le y)$, the p_{th} quantile of *Y* is defined as the inverse function

$$Q(p) = \inf\{y : F(y) \ge p\}, \quad 0 < p < 1 \qquad (1)$$

In particular, the median is Q (.5).

Following Koenker and Bassett (1978), the quantile regression equation is specified as

$$\ln y = X'\beta^p + \varepsilon^p \qquad (2)$$

$$Q^p(\ln y \mid X) = X'\beta^p$$

Thus, the conditional p_{th} quantile is determined by the quantile-specific parameters, β^p, and a specific value of the covariate vector *X*.

A quantile *p* can be viewed as a position in the distribution that minimizes an average weighted distance, with weights (ρ) depending on whether the point is above or below the value *p*. The p^{th} regression quantile, 0<*p* <1, is defined as a solution to the problem:

$$\min_{\beta \in R}\left\{\sum_{i:y_i \ge X_i\beta} \rho\left|\ln y_i - X_i\beta_p\right| + \sum_{i:y_i < X_i\beta}(1-\rho)\left|\ln y_i - X_i\beta_p\right|\right\}$$

or

$$\min_{\beta \in R}\left\{\sum_i \rho_p\left(\ln y_i - X_i'\beta_p\right)\right\} \qquad (3)$$

Here, $\rho_p(z) = z(p - I(z < 0))$, *I* (.) denotes the indicator function.

Thus, the linear conditional quantile function, $Q^p(\ln y \mid X) = X'\beta^p$, can be estimated by solving

$\hat{\beta}^p = \arg\min_{\beta \in R} \sum_{i=1}^{n} \rho_p\left(\ln y_i - X_i'\beta\right)$, for any quantile $p \in$ (0,1), $\hat{\beta}^p$ is called p_{th} regression quantile. For, p=.5 which minimizes the sum of absolute residuals, corresponds to median regression, which is also known as L_1 regression.

For a random sample {y_1, ..., y_n} of Y , it is well known that the sample median is the minimizer of the sum of absolute deviations

$$\min \sum_{i=1}^{n} \left| \ln y_i - X'\beta^{p}{}_i \right|$$
$$\beta \in R$$

Thus, the estimator for the median-regression model is obtained by minimising

$$\sum_i \left| \ln y_i - X_i'\beta \right|$$

Under appropriate model assumptions, as the sample size is very large, we obtain the conditional median of *y* given *x* at the population level. The median regression is the maximum likelihood estimate for the double-exponential distribution. The median-regression line, must pass through a pair of data points with half of the remaining data lying above the regression line and the other half falling below. That is, roughly half of the residuals are positive and half are negative.

Quantile regression inherits certain robustness properties of the ordinary sample quantiles. Estimation by OLS assumes that the marginal impact of education on log-wages is constant over the log-wage distribution. In this case, the effect of having one additional level of education can be represented by a shift (to the right) of the conditional log-wage distribution. Quantile returns, in turn, measure the wage effect of education at different quantiles, thus describing changes not only in the location but also in the shape of the distribution. While OLS returns measure the average differential between education groups, differences in quantile returns represent the wage differential between individuals that are in the same group but located at different quantiles. The estimates and the associated inference apparatus have an inherent distribution-free character since quantile estimation is influenced only by the local behaviour of the conditional distribution of the response near the specified quantile.

3. Data

We have used unit level data from 38th round, 50th round, 61st round and 68th round survey on employment and unemployment situation in India (Schedule 10) for the period 1983, 1993-94, 2004-05 and 2011-12 respectively provided by the NSSO. The cross-sectional survey is roughly representative of the national, state, and the so-called "NSS region" level. It gathers information about education and demographic characteristics of household members, weekly time disposition, and their main and secondary job activities. The principal job

activities are defined for all household members as self-employed, regular salaried worker, casual wage labourer and so on. Per capita monthly consumption expenditure on all goods and services is used as a proxy for income per person within a household. Wages are given in cash and kind, both in value terms, on weekly basis for persons by their usual activity status of employment. We have used wage total, by adding wage in cash and wage in kind, to estimate earnings inequality in the labour market.

We have constructed random pooled sample of unit level information by taking four different samples of the survey rounds mentioned above drawn independently from the same population at different points of time. The nominal values of consumption expenditures and wages at different survey rounds are converted in to real terms by deflating with consumer price index for the corresponding period with the same base (2000-01). We restrict the sample to wage earners aged between 15 and 60, the working age in the Indian labour market. Thus, self-employed own account workers, students and unpaid family worker have been excluded from the sample.

4. Occupational status and employment characteristics

Employment status or occupational status of households is useful, although roughly, in analysing employment characteristics in an economy. The households in our data set are categorised on the basis of major source of earnings of the household members. In the rural economy, employment status of the households is classified broadly into farm and non-farm employment. Farm employment is further divided into self-employment in agriculture (a part of them are cultivators), agricultural workers and other workers. Rural non-farm employment is classified again into self-employment in non-agriculture, casual workers and other workers. In the urban economy, households by employment type are classified as self-employed, wage earners on regular basis and wage earners on casual basis. Tables 1a and 1b present the changing pattern of employment share of different types and the corresponding share of their income[2] of the rural and urban households respectively over different rounds of employment and unemployment survey by the NSSO since the early 1980s.

[2] As there is no income information as such in the employment and unemployment survey in India, we have used monthly per capita expenditure as a proxy for income.

The figures shown in Table 1a clearly suggest that the structural transformation of employment and income occurred in the rural economy from the farm to non-farm sector. Non–farm employment in the rural economy assumes significance in creating new jobs as well as diversification of jobs away from agriculture in a transitional economy like India. While the agricultural households have been dominating in the rural economy, the share of employment in agriculture, both as self-employed and casual labour, and the corresponding income share declined systematically since the early 1980s. The scope of getting job in the non-farm sector in rural India increased with growth and development and the observed statistics as displayed in Table 1a support this fact. Self-employment in non-agricultural activities, may be in the form of street vendors to shopkeepers or even high skilled professional, increased till 2005 and stagnated thereafter. The share of casual workers in the non-farm sector, on the other hand, increased significantly over the survey rounds.

Table 1a Changes in employment and income shares in rural India

	Employment share				Income* share			
	1983	1994	2005	2012	1983	1994	2005	2012
Self-employed in agriculture	55	47	44	41	53	51	46	42
Self-employed in non-agriculture	10	13	17	17	10	14	18	18
Regular wage earning				9				12
Casual labour in agriculture	25	24	22	17	27	19	17	14
Casual labour in non-agriculture	5	7	10	13	4	6	9	11
Others	5	9	8	3	6	11	10	3

Note: Monthly per capita consumption expenditure is used as a proxy for income
Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

The urban households are mostly engaged in non-farm employment in the form of self-employment followed by regular wage or salaried workers. Self-employment in the urban sector is more heterogeneous than in the rural sector. It ranges from street vending to high skilled professional in finance or IT. The share of self-employment in urban households increased during 1993-2005, but declined thereafter. While the share of wage earners on regular basis remained stagnant in the urban sector, the share of casual workers increased during 2005-2012. Thus, the casualization of employment increased in the non-farm sector both among the rural and urban households. The expansion of employment on permanent basis is restricted mainly for a very few well-endowed groups of workers keeping a large proportion remained in low productive informal employment on casual basis. It results in widening wage gap between farm and non-farm sectors, and even between different segments within the non-farm sector in the economy.

Table 1b Changes in employment and income shares in urban India

	Employment share				Income share			
	1983*	1994	2005	2012	1983	1994	2005	2012
Self-employed	45	43	48	46	44	41	45	44
Regular wage earning	0	41	37	37	0	47	44	44
Casual labour	0	12	11	13	0	8	7	8
Others	55	4	3	4	56	4	4	5

Note: In 38th round survey household types are categorised into self-employment and other workers.
Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

The employment characteristics and segmentation of the Indian labour market can be looked at in a more meaningful way by analysing the status of employment of the workers by their levels of education. Human capital, particularly education, is very much crucial in explaining earnings inequality through labour market characteristics. The human capital theory suggests that education and training would improve workers' skills, enabling them to work in the nonfarm sector for higher wage. To understand better the dynamics of inequality and employment characteristics we have shown the distribution of wage workers by levels of education over different time points, and the status of employment of wage earners by their education (Tables 2a and 2b) in 2012.

The composition of wage earners in terms of their levels of education has changed in the Indian labour market since the early. The share of workers in lower strata in terms of their education level had declined and the share of those with higher levels of education increased significantly over time. The share of graduate and post-graduate workers increased spectacularly during the period 1983-2012. In India, by taking both the rural and urban sector together, about one-fourth of the wage earners were educated at secondary or higher secondary level while one fifth of wage workers were illiterate and just above 17 percent had education level graduate and above in 2012.

Table 2 Distribution of wage workers by levels of education in India

Education level	1983	1994	2005	2012
Not literate	49.2	36.8	28.0	20.6
Below primary	23.0	11.1	9.8	8.2
Primary	12.2	12.1	12.7	11.2
Middle	10.8	13.5	16.9	17.1
Secondary	0.3	17.0*	19.3*	25.3*
Graduate and above	4.5	9.5	13.4	17.6

Note: * includes both secondary and higher secondary levels
Source: Author's calculation from 38th, 50th, 61st and 68th rounds of NSSO

However, the accumulation of human capital through education is no longer a guarantee of getting better quality job. There are many socio-economic and cultural factors that actually restrict the vulnerable people to enter into higher hierarchy employment. In many cases, certain groups of workers are segregated from better jobs because they are less acceptable socially rather than because they lack ability. Moreover, in recent years the nature of jobs has changed dramatically because of pro-business market openness and deregulation of labour market in transitional economies. Labour market flexibility enhances the peripheral segment of the labour market by reducing the core segment of it. The distribution of workers by their status of employment and education for 2011-12 as shown in Tables 3a and 3b for rural and urban areas respectively support indirectly these facts.

Majority of the rural working people with no education or schooling up to primary education were absorbed as casual workers in non-farm activities followed by self-employment in farming. A significant part of the persons with schooling up to primary level, however, were engaged in self-employment in the non-farm sector. Rural people who have education the middle school or secondary level were mostly engaged in self-employment group either in the farm or non-farm sector. While the majority of the working age people in the rural economy with higher level of education (higher secondary, diploma, graduate, post-graduate and above) absorbed as wage or salaried workers on regular basis in the non-farm sector, a notable shares of them engaged as self-employed or family workers.

Table 3a Distribution of educated working age people by types of employment in rural India: 2011-12

	Not literate	Below primary	Primary	Middle	Secondary	Higher secondary	Diploma course	Graduate	Postgraduate and above	All
Farm sector										**39.1**
Self employed	27.2	51.4	23.6	22.9	22.1	18.4	8.4	12.4	8.5	22.7
Family worker	17.8	25.0	15.2	15.6	16.6	17.1	7.3	10.3	5.7	15.4
Regular wage worker	0.1	0.4	0.2	0.3	0.3	0.5	0.6	0.4	0.1	0.2
Casual wage worker	1.0	1.9	1.0	0.9	0.4	0.2	0.2	0.2	0.0	0.7
Non-farm sector										**60.9**
self employed	14.7	41.7	21.7	22.1	22.8	19.3	17.4	17.4	12.7	19.4
Family worker	4.2	7.7	4.9	5.8	5.5	5.9	2.9	4.2	2.0	4.8
Regular wage worker	4.4	14.7	9.0	12.8	19.8	31.5	58.0	52.9	69.9	16.6
Casual wage worker	30.6	54.7	24.5	19.7	12.7	7.0	5.2	2.3	1.1	20.1

Source: Author's calculation with 68th round unit level NSS data

Table 3b displays the distribution of working age people with different levels of education by types of employment in urban India during 2011-12. Majority of the urban

working people with no education or schooling up to primary education or middle school education were absorbed as own account workers in informal activities like small trading or street vending. More than one fourth of the people without any formal or informal education worked very indecent activities including begging as indicated by other workers in the data set. Roughly one fifth of these people were absorbed in wage employment on casual basis in the private sector activities. A significant part of the persons with schooling up to middle school level were either regular wage worker or casual wage worker of the private sector. The share of regular wage employment increased with the level of education. Nearly three fourth of the urban people who have education at post-graduation or above were mostly engaged in wage employment on regular basis. The shares of this type of employment for graduate workers, and workers with diploma holders were just above 60 percent and 70 percent respectively. However, a significant part of the workers with higher level of education (higher secondary, diploma, graduate, post-graduate and above) were self-employed as own account worker. Thus, the distribution of workers by human capital across different employment categories in urban India also supports the facts we have mentioned above.

Table 3b Distribution of working age people with different level of education by employment type in urban India: 2011-12

	Not literate	Below primary	Primary	Middle	Secondary	Higher secondary	Diploma course	Graduate	Postgraduate and above	All
Own account worker	27.0	32.7	33.5	35.3	37.7	34.3	18.9	25.1	18.0	30.7
Employer	0.4	0.8	1.1	1.5	2.4	2.5	2.2	3.1	2.3	1.8
Unpaid family worker	7.1	8.3	9.1	10.4	9.1	10.4	3.8	7.4	4.2	8.4
Regular worker	17.5	22.1	29.1	33.2	38.3	46.1	70.1	61.7	74.1	39.3
Casual worker in public sector	0.7	0.6	0.7	0.5	0.2	0.2	0.1	0.0	0.0	0.4
Casual worker in private sectors	20.5	21.3	19.9	14.9	8.5	3.9	3.6	1.3	0.3	11.4
Others	26.8	14.3	6.7	4.2	3.8	2.4	1.2	1.4	1.1	8.0
All	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Source: As for Table 3a

5. Inequality by employment types

The growth of international trade, declining unionization and real minimum wage, rising immigration, and technological change may be responsible for rising inequality globally. Skill-biased technological change has been an important determinant of rising

inequality experienced by the developing countries after opening of their domestic market to the global one (Johnson 1997). Technological change of this type has enhanced employment and wages of skilled workers while depressing the employment opportunities and earnings of the less-skilled. Increasing trade openness in India is associated with increasing labour productivity and also wage inequality among skilled and unskilled workers in the organised manufacturing sector (Galbraith et al. 2004, Dutta 2005, Das 2007)).

We analyse here how inequality has changed with employment characteristics over the new growth regimes in India that started in the early 1980s. The structural break in economic growth appeared in the Indian economy much before the 1991 reforms (Wallack 2003, Das 2007a). The new economy of the 1980s and 1990s, even as it delivered faster growth on average, ensured higher proportional rates of growth of top incomes as compared to the first three decades of planning. In the early 1990s, the economy of the country opened its doors to the world. Subsequently, people with accumulated, or inherited wealth benefited the most from the openness of this kind. The pro-business policies made more wealth for the upper end while the lower end dropped down further into oblivion increasing the between group inequality.

We use Gini index to measure inequality and decompose it into within group and between group inequality[3]. The index is decomposed by employment status of the households

[3] The Gini index for subgroup j is given by

$$G_{jj} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}\left(y_{ij} - y_{rj}\right)}{2n_j^2\bar{y}_j}$$

The within group inequality index is the sum of Gini indices for all subgroups weighted by the product of population shares and wage shares of the subgroups:

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j$$

If the population share and wage share in sub group j are $p_j = \frac{n_j}{n}$ and $s_j = \frac{p_j\bar{y}_j}{\bar{y}}$ respectively, the contribution to total inequality attributable to the differences between the k population subgroups is

$$G_b = \sum_{j=1}^{k}\sum_{\substack{h=1 \\ j\neq h}}^{k} G_{jh} D_{jh}(p_j s_h + p_h s_j)$$

If subgroups are non-overlapping, total inequality can be expressed as the sum of within group and between group indices. The groups are non-overlapping means each individual's wage income in one group is greater or

(Tables 4a and 4b) as well as by level of education of the working people (Tables 5 and 6) at different time points corresponding to NSSO survey rounds on employment and unemployment situation in India. As there is no income survey data in official statistics in India, poverty and inequality have conventionally been measured by using consumer expenditure survey data. Income inequality measured with data from the household consumer expenditure survey underestimates the inequality as observed in reality for two reasons: a very little share of income is spent as consumption expenditure by the rich and a very small share of the rich or ultra-rich people is covered in the sample.

In the rural economy, overall inequality among households with different status of employment declined significantly during 1983-1994 and declined further in 2005, but increased during 2005-2012 (Table 4a). While within group inequality declined, the between group inequality increased markedly during the 1990s. The within group inequality declined at the highest rate among agricultural workers followed by cultivators and self-employed in non-agriculture in this period. The inequality of this kind, although declined initially during the high growth phase of post-reforms development, increased among every household group categorised by employment status and at higher rates among agricultural households during 2005-2012.

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lower than each individual in the other groups. But, if the subgroups are overlapping, Dagum (1997) suggests another component of inequality measuring the contribution of the intensity of transvariation. This component is a part of the between-group disparities issued from the overlap between the two distributions. The contribution of the transvariation between the subpopulations to G:

$$G_t = \sum_{j=1}^{k} \sum_{\substack{h=1 \\ h \neq k}}^{k} G_{jh} \left(1 - D_{jh}\right) \left(p_j s_h + p_h s_j\right)$$

Thus Gini index can be decomposed into three components: within group inequality, between group inequality and inequality due to group overlapping:

$$G = G_w + G_b + G_t$$

Table 4a Gini index of monthly per capita consumption expenditure by household status of employment in rural India

Employment status	1983	1994	2005	2012
self-employed in agriculture	0.42	0.27	0.24	0.28
Self-employed in non-agriculture	0.41	0.27	0.26	0.28
Regular wage earners				0.29
Casual labour in agriculture	0.53	0.24	0.2	0.24
Casual labour in non-agriculture	0.34	0.26	0.23	0.25
Others	0.47	0.3	0.31	0.33
Within group inequality	0.16	0.08	0.07	0.07
Between group inequality	0.04	0.07	0.08	0.07
Overlapping group inequality	0.25	0.12	0.11	0.14
All	0.45	0.28	0.26	0.28

Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

The changing pattern of inequality among the urban households by their occupational status is shown in Table 4b. We observe that the incidence of inequality was higher in the urban economy as compared to the countryside. Although inequality among urban households declined during 1983-1994 by following the trend in rural economy, the rate of decline was very slow. The fall in overall inequality among the urban households during this period was mainly because of the fall in within group inequality. The between group inequality, on the other hand, increased till 2005 and remained at the same level thereafter. The within group inequality also show the similar pattern of change during the post-reforms period. The within group inequality increased at a higher rate among regular wage earners than the self-employed group during the initial decade of reforms. Surprisingly enough, the inequality among casual workers declined in this period, although increased later on.

Table 4b Gini index of monthly per capita consumption expenditure by household status of employment in urban India

	1983	1994	2005	2012
Self-employed	0.38	0.32	0.34	0.35
Regular wage earning		0.31	0.35	0.35
Casual labour		0.24	0.21	0.26
Others	0.39	0.34	0.40	0.37
Within group inequality	0.19	0.12	0.13	0.13
Between group inequality	0.02	0.08	0.1	0.1
Overlapping group inequality	0.17	0.12	0.12	0.13
All	0.39	0.33	0.35	0.36

Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

Human capital, particularly education, is one of the major determinants of employment characteristics. According to human capital theory, persons with higher education have more chance to get better quality jobs with higher pay. Thus, unequal access to education may be one of the sources of inequality. To understand, at least grossly, how inequality changes with levels of education we have estimated Gini index of per capita consumption expenditure among working age people by education level over time (Table 5). The Gini indices calculated from per capita monthly consumption expenditure as provided in 61st round (2004-05) and 68th round (2011-12) survey data suggest that inequality increases with education level. The inequality index from 50th round (1993-94) survey reveals that the incidence of income inequality started to increase with education level after middle school level, while the inequality index calculated from 38th round (1983) survey data declined with education from primary level and above. Thus, the relationship between inequality and education is significantly different in the post-reforms period as compared to the pre-reforms era. Higher the level of education higher is the inequality may be because of skill biased technological change that appears during the pro market reforms.

Table 5 Gini index of monthly per capita consumption expenditure among working age people by education

Education level	1983	1994	2005	2012
Not literate	0.46	0.30	0.26	0.30
Below primary	0.45	0.30	0.28	0.31
Primary	0.47	0.30	0.28	0.30
Middle	0.45	0.30	0.44	0.31
Secondary	0.40	0.33	0.50	0.33
Graduate and above	0.34	0.37	0.35	0.36
All workers	**0.47**	**0.34**	**0.36**	**0.34**
Within group	0.28	0.13	0.11	0.10
Between groups	0.17	0.55	0.78	0.55
Overlapping groups	0.55	0.31	0.10	0.35

Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

Income inequality among workers with similar education declined during 1983-1994, but increased during 1994-2005 mainly because of the rise in inequality at middle and secondary levels of education. If overall inequality is decomposed into within group and between group parts on the basis of education level of workers we observe that the contribution of within group inequality to overall inequality declined over time, but, the contribution of between group inequality increased enormously during 1983-2005. However,

the contribution of between group inequality dropped down during 2005-2012 by following the trend in within group inequality.

Wage is the primary source of income for workers and wage inequality is used conventionally as alternative to income inequality where income data are not readily available. Table 6 displays earning inequality measured by Gini index of weekly wages among workers across education level over time. Wage inequality was the highest among workers with education at middle school level followed by primary or below primary level of education in 2012. Inequality in wage was the lowest among graduate or post-graduate workers during this period. Wage inequality for all workers declined, but very slowly during 2005-2012. The rate of decline of wage inequality was different for different groups of workers by their education level. Skills are positively but imperfectly associated with educational attainment. This imperfect association between skill and education may lead to larger wage gaps between education groups as well as within education group.

Table 6 Gini index of weekly wages by education

Education level	1983	1994	2005	2012
Not literate	0.83	0.66	0.48	0.45
Below primary	0.83	0.71	0.51	0.48
Primary	0.84	0.71	0.50	0.48
Middle	0.73	0.70	0.48	0.49
Secondary	0.76	0.64	0.46	0.47
Graduate and above	0.83	0.51	0.38	0.40
All workers	**0.84**	**0.73**	**0.53**	**0.51**
Within group	0.21	0.12	0.10	0.10
Between groups	0.35	0.54	0.60	0.56
Overlapping groups	0.44	0.34	0.30	0.33

Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

The relative contributions of within component and between components of Gini index are important in explaining the changes in overall inequality. Decomposition of wage inequality by sub-population reveals that a significant part of wage inequality as observed in India is accounted for by inequality 'between' groups rather than inequality 'within' group for every type of working people (Das, 2012). In this study, Gini index of weekly wages is decomposed into 'within' group, 'between' group and 'overlapping' group components. The estimated results shown in the lower panel of Table 6 suggest that wage inequality by education in Indian labour market has been driven primarily by growing dispersion among workers between education groups rather than within education group. In 2012, more than 56

percent of the variance of weekly wage earnings can be attributed to between education groups variation. More importantly, this share grew over different NSSO rounds as shown in Table 6 suggesting that the major part of the change in overall wage variance was due to wage disparity among workers between education groups.

The incidence of income inequality in terms of consumption expenditure of workers by education level is less than inequality in wage earnings for obvious reasons. While wage inequality reduced after 1994, income inequality did not follow similar trend during this period. Indeed, consumption or income inequality increased with level of education contrasting to the case of wage inequality. Thus, the distribution of non-wage income may be crucial in explaining rising income inequality with education.

6. Effects of employment characteristics on earnings

To locate the possible factors for observed inequality as described above we have estimated conditional earnings at quantiles 0.10, 0.25, 0.50, 0.75, and 0.90 denoted respectively by Q_{10}, Q_{25}, Q_{50}, Q_{75}, and Q_{90}. The sample observations used in estimating quantile regression are obtained by pooling of four independent samples at four different time points (1983, 1993-94, 2004-05 and 2011-12) taken from the same population. We have taken real weekly wage as a response variable (y). The predictors are the variables, both qualitative and quantitative, that capture different dimensions of employment characteristics (X). The regression model at quantile *p* is specified as

$$y = \beta_0^p + \sum_i \beta_{1i}^p D_{year} + \beta_2^p D_F + \beta_3^p D_R + \sum_j \beta_{4i}^p D_{ES} + \beta_5^p age + \beta_6^p D_{TE}$$
$$+ \sum_k \gamma_k^p D_{edu} + \sum_{l,j} \eta_{i,j}^p D_{year} D_{ES} + \sum_{i,k} \eta_{i.k}^p D_{year} D_{edu} + \varepsilon^p$$

Here, D_{year}, year = 1983, 4005, 2012, is a time dummy measuring the effect over time, D_F is a female dummy used for detecting gender gap in earnings, D_R is a dummy variable for capturing rural urban difference, D_{ES} is used to capture earnings difference for workers with different employment status, age is used as a proxy for work experience, D_{TE} is a dummy for workers with technical education, D_{edu} denotes education dummy. We also incorporate interaction dummies to estimate the change in earnings over time for different types of

workers and different education level. Here, $0 < p < 1$ indicates the proportion of the population having scores below the quantile at *p*. The ε^p is independently and identically distributed random error.

The estimated results are shown in Table 7. The quantile regression parameter estimates the change in a specified quantile of the response variable produced by a one unit change in the predictor variable. It allows comparing how some quantiles of the wage may be more affected by education and employment status than other quantiles. The intercept term shows the real weekly wages at different percentiles of the sample in the absence of effect of any predictor incorporated in the model in 1993-94. The real wage earnings at 90th percentile was more than 2.5 times the median wage earnings and more than 8.5 times the wage at the 10th percentile implying significant wage gap in the Indian labour market. The three time dummies used in the model measure the time effect of wage earnings. The year 1993-94, just after the initiation of liberalising policy, is used as a reference time of analysis. The coefficients of the time dummies suggest that real wages increased after 1993-94 and relatively at higher rates at the upper percentiles. Thus the wage gap between workers at different percentiles increased over time during the post-reforms period. Age of the workers, a proxy for experience, had significant positive effect on wage at every percentile, but at higher proportional rate up to 75th percentile. The rural-urban earnings differential and gender gap in wage earnings were significantly high at the upper end of the wage distribution. A significant wage premium was observed for workers with technical education at every location of the wage distribution. The wage gap among workers because of the differences in technical knowhow is an indication of skill biased technological change during the post-liberalisation period.

The level of education has favourable effect on wage income. To look at how workers' education has had impact on wage earnings we have taken workers with no education as a reference group and compared wage earnings across workers with different levels of education by incorporating education dummies. The estimated results suggest that higher the level of education, higher is the wage earned by the workers supporting the hypotheses put forward in the human capital theory. As shown in Table 7 the weekly wage increased with education at a higher proportional rate at higher percentiles in the wage distribution. For example, the conditional weekly wages for workers with education level graduate and above was higher by Rs.1359.15 than the wage for illiterate workers at 90th

percentile, while the wage gap between the similar workers group was Rs.151.63 at 10th percentile. The estimated coefficients of education at every level were increasing over the quantiles of wage distribution implying that education had positive impact on inequality. As returns to education at a particular education level were higher at the upper quantiles, the wage distribution became more unequal because of education. Dispersion of wages across quantiles was relatively small in the below primary level and remarkably large in the graduate or post-graduate level. In other words, the impact of education on within-group inequality was the highest at the graduate or post-graduate level and was the lowest at below primary level. The coefficients of interaction dummies for time and education at graduate and above demonstrate that the dis-equalising effect of higher education escalated over time. The effect of education at secondary or higher secondary level on wage reduced at 25th percentile point, but increased significantly at the upper percentile points over the period between 1993-94 and 2011-12. Thus, earnings inequality between different groups of workers even at the same level of increased over time during the post-reforms period.

Inequality in earnings is observed across different status of employment partly because of the differences in educational qualifications of the workers. Wage workers engaged on regular basis were better off at every location of wage distribution than other types of workers. Workers endowed with higher education mainly from the upper social status are engaged in better quality jobs. But, the casual wage workers, the majority of them are vulnerable, earned lower income than other types of working people particularly at 90th percentile level.

One can reconcile wage inequality across education with labour market segmentation by types of employment. Labour market in India is segmented between the core (formal) and the periphery (informal) sectors consisting of permanent employment with high wage and contractual employment with low wage respectively. Working conditions in the core segment are better in terms of wages and social security benefits than those in peripheral employment. The expansion of non-farm employment opportunities is restricted for a very few well-endowed groups of workers keeping a large proportion remained in low productive informal employment. It results in widening wage gap between farm and non-farm sectors, and even between different segments within the non-farm sector. While higher level of education enables people to increase their chances of having access to employment by enhancing the quality of their job search, there are many socio-economic and other restrictions for the lower strata of the people to enter into higher hierarchy employment.

Table 7 Quantile estimates of returns to education

Real wage	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
Intercept	50.89***	96.79***	173.67***	268.00***	442.55***
age	0.57***	1.11***	2.27***	4.53***	5.95***
D_1983	-4.52	-9.35	-28.92	-51.08	-96.65*
D_2004	94.72***	154.69***	254.59***	588.66***	1238.74***
D_2011	181.75***	289.56***	425.79***	809.44***	1812.05***
D_rural	-33.02***	-58.88***	-103.72***	-171.45***	-246.12***
D_female	-23.39***	-38.52***	-56.35***	-73.97***	-95.35***
D_tech_edu	60.24***	180.00***	330.61***	508.11***	749.15***
D_below_primary	9.56***	16.78***	31.37***	53.37***	66.56***
D_primary	13.07***	21.31***	43.42***	81.66***	108.41***
D_middle	25.40***	46.39***	94.44***	193.72***	217.97***
D_secondary	70.61***	162.04***	349.28***	456.38***	521.93***
D_graduate	151.63***	530.15***	777.76***	1032.14***	1359.15***
D_regular_wage	80.85***	146.29***	222.94***	277.10***	299.61***
D_casual_wage	40.60***	46.61***	34.01***	5.62	-45.63*
D_1983_D_graduate	-105.38***	-480.50***	-553.98***	-588.59***	-734.27***
D_2004_D_graduate	61.34***	46.94***	415.22***	636.05***	639.66***
D_2011_D_graduate	90.08***	41.21***	689.69***	1151.88***	1024.16***
D_1983_D_se_hse	-43.52***	-133.61***	-261.74***	-244.97***	-241.62***
D_2004_D_se_hse	8.37*	-10.12	96.15***	382.63***	334.02***
D_2011_D_se_hse	17.65***	-28.24***	2.68	550.58***	404.77***
D_1983_D_regular_wage	-94.29***	-163.48***	-208.40***	-258.57***	-282.29***
D_2004_D_regular_wage	-78.58***	-153.93***	-276.34***	-493.69***	-825.58***
D_2011_D_regular_wage	-94.36***	-185.47***	-325.71***	-537.30***	-852.34***
D_1983_D_casual_wage	-22.80**	-30.78**	-24.19	-7.46	25.60
D_2004_D_casual_wage	-78.67***	-130.68***	-220.22***	-534.27***	-1152.42***
D_2011_D_casual_wage	-85.19***	-145.33***	-243.88***	-574.79***	-1489.18***
Pseudo R^2	0.0634	0.1125	0.2025	0.2943	0.3532

Note: *** significant at less than 1 percent level, ** significant at 5 percent level, the rest are statistically insignificant

Source: Author's calculation with data from 38th, 50th, 61st and 68th rounds of NSSO

7. Conclusions

The prevalence of inequality and poverty varies not only from one society to another but also from one group to another group of people within a society. Inequality in status and power restricts more the choice of the poor. The gap in income between those who are at the top stratum and at the bottom will increase the vulnerability of the later. This is because more

inequitable system provides better and more opportunities to the rich enjoying hegemony in different forms in the society over the poor.

In this study, we have analysed how inequality has changed with employment characteristics over the new growth regimes in India that started in the early 1980s by using Gini index and decomposing it into within group and between group inequality. While within group inequality declined, the between group inequality increased markedly during the 1990s and became stagnant thereafter in the rural economy. The incidence of inequality was higher in the urban economy as compared to the countryside. The within group inequality increased at a higher rate among regular wage earners than the self-employed group during the initial decade of reforms.

We observe that structural transformation of employment and income occurred in the rural economy from the farm to non-farm sector. The scope of getting job in the non-farm sector in rural India increased with growth and development mainly in the form of casual employment. The casualization of employment increased in the non-farm sector both among the rural and urban households. While a very few people are well-endowed for permanent wage employment, a very large proportion remained in low productive informal employment on casual basis. It results in widening wage gap between farm and non-farm sectors, and even between different segments within the non-farm sector in the economy.

Worker's education is important in explaining employment characteristics as well as earnings inequality. The major share of workers in the Indian labour market is either illiterate or educated at secondary or higher secondary level. However, the accumulation of human capital through education is no longer a guarantee of getting better quality job. A notable shares of the working age people both in the rural and urban economy with higher level of education engaged as self-employed or family workers. Unequal access to education may be one of the major sources of inequality. The relationship between inequality and education is significantly different in the post-reforms period as compared to the pre-reforms era. Higher the level of education, higher is the inequality may be because of skill biased technological change that appears during the pro market reforms.

As wage is the primary source of income for workers and wage inequality is used in this study as alternative to income inequality. Wage inequality was the highest among workers with education at middle school level and the lowest among graduate or post-graduate workers in 2012. Wage inequality declined but at different rates for different groups

by education. Wage inequality by education in Indian labour market has been driven primarily by growing dispersion among workers between education groups rather than within education group. To locate the possible factors for observed inequality as described above we have estimated conditional earnings at different quantiles. The wage gap between workers at different percentiles increased over time during the post-reforms period. The rural-urban earnings differential and gender gap in wage earnings were significantly high at the upper end of the wage distribution. The estimated results suggest that higher the level of education higher is the wage earned by the workers supporting the hypotheses put forward in the human capital theory. As returns to education at a particular education level were higher at the upper quantiles, the wage distribution became more unequal because of education and the effect was escalating over time. Earnings inequality between different groups of workers even at the same level of education increased over time during the post-reforms period.

The first three decades of planning (1950s to 1970s) in India was associated with a marked decrease in inequality that had prevailed during the colonial period. The situation, however, changed dramatically in the early 1980s, which marked the turning point for the dynamics of income inequality in India and indeed across the world. The new economy of the 1980s and 1990s, even as it delivered faster growth on average, ensured higher proportional rates of growth of top incomes as compared to the first three decades of planning. The pro-business policies made more wealth for the upper end while the lower end dropped down further into oblivion increasing the between group inequality.

There is little disagreement that poor from all social strata have not been equally benefited by the faster growth as appeared since the early 1990s. Among the poor the worse sufferers continue to be from the socially disadvantaged groups like Scheduled Castes and Scheduled Tribes. Within the neo-liberal framework the state guarantees property rights and maintenance of macroeconomic stability, but ignores redistribution of growth, nationally and internationally. It also ignores relative inequality in income, assets and opportunities, social and economic security, insecurity of job, income and health.

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