Chapter 10
Structural Transformation of Employment and Wage Inequality in the High Growth Regime: A Study with Micro-Level Data in India

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Abstract This study explores how inequality in wage income is associated with workers' human capital and employment status during the high growth regime that started in the early 1980s in India, with household and personal-level information from employment and unemployment survey. The study observes that 'within' group inequality declined very slowly, but the 'between' group inequality increased markedly during this period. Conditional wage earnings at different quantiles have been estimated to locate the possible effects of human capital, particularly education and employment characteristics. The study observes that the wage gap between workers at different percentiles increased over time during the high growth regime, and at a higher rate at the upper end of the wage distribution. The workers' schooling has favourable effect on wage income as expected. Wage income is increased with higher level of education at a higher proportional rate at higher percentiles in the wage distribution. As returns to education have significant impact on wage income, the wage distribution became more unequal because of the difference in access to education.

10.1 Introduction

The development experience of Asian developing countries is different from what was observed in the developed countries during the golden era of capitalist development.[1] In the OECD countries, the share of agriculture in total output and employment

[1] The process of development of the OECD countries has been experienced with increasing inequality in the initial stages and declining it in the latter stages with the transfer of labour from low-productive agricultural activities to relatively high-productive manufacturing (Kuznets 1955). Inequality increases in the first stage of growth, especially when it involves gradual migration from the rural areas to the urbanised sectors where differential access to finance, education and job opportunities is associated with greater inequality. But, after decades of growth, the wages in low-income rural sector would increase possibly because of the adaption of better technologies in farming, leading to the fall in inequality.

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declined with growing importance of industries and then services. While structural change appears in GDP in the Asian economies by following roughly the similar pattern as observed in the OECD countries, there has been no significant structural transformation in employment matching with the change in output share in many Asian countries. In India, for example, the fall in output share of agriculture has not been accompanied by the proportionate fall in employment share implying that income per capita in agriculture has been declining. In services, on the other hand, there has been no significant growth of employment despite its higher proportional output growth indicating increasing per capita income in the services sector. No significant transference of labour from land-based activities to manufacturing or services has been observed in the Indian economy (Das 2007a). The failure of manufacturing to absorb the growing labour force has likely consequences in the distribution of labour income in the Asian economy. The inherent differences in the changes in structural characteristics of employment between the Asian developing nations and the post-war Western European countries may lead to different distributional outcomes in labour income between these two groups of economies.

In the context of this type of structural changes in employment and output in India, this chapter analyses the distribution of wage income over the new growth regime in India that started in the early 1980s. The structural break in economic growth appeared in the Indian economy in 1983, much before the 1991 reforms (Wallack 2003; Das 2007b). The early 1980s also marked the turning point for the dynamics of income inequality in India and indeed across the world. While average income grew faster since the mid-1980s than it had in the planning period,[2] inequality increased rapidly primarily because of an enormous increase in incomes at the top, particularly incomes at the very top (Basole 2014). The top 1% in income distribution owned roughly 9% of the national income in India in the late 1990s (Banerjee and Piketty 2005; Chancel and Piketty 2017).

The new economy of the 1980s and 1990s exhibited higher proportional rates of growth of income at the top percentiles than the growth rates at the bottom level ensuring increasing inequality during the high growth regime. 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 increasing the "between" group inequality enormously. Skill-biased technological change has been an important driving force of rising inequality experienced by the developing countries after the opening of their domestic market to the global one (Johnson 1997). Technological change of this type has enhanced the 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 between

[2]The first three decades of planning (1950s–1970s) were associated with a marked decrease in inequality that had prevailed during the colonial period in India. In particular, the growth rates of real income of the rich, the super-rich, and the ultra-rich, as defined in Banerjee and Piketty (2005), declined significantly, even as average income grew slowly.

skilled and unskilled workers in the organised manufacturing sector (Galbraith et al. 2004; Dutta 2005; Das 2007c).

Accumulation of skill through education and training enables workers to get job in the high-skilled high-productive sector for higher wage. 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 schooling increase with skill-biased technical change demanding more skilled workers. Thus, human capital, particularly education, is very much crucial in explaining inequality in wage income, particularly during the technology-driven new growth phase.

This study estimates the extent of inequality in wage income and examines how it is associated with employment characteristics and workers' human capital by applying quantile regression model using the survey data from India during the period when transformation has been started from planning-based development to market-oriented development through the growing integration of the domestic economy into global trade and financial system.[3] Structural transformation of such type has a far-reaching impact on inequality in wage income. Using the survey data at different time points during the past three decades (1983–2012), this study observes that inequality in wage income increased partly because of inequality in workers' education, and the effect is dissimilar across different workers' group with different employment characteristics at different locations of the wage distribution. The differences in wage income across quantiles are substantially higher for workers with education-level graduate and above than for less-educated workers.

The study is organised into six sections. After some introductory remarks in Sect. 10.1, Sect. 10.2 describes, in short, the data used in this study. Section 10.3 discusses the econometric methodology applied to analyse the disproportional effects of returns to schooling and employment characteristics on conditional wage. Some observed facts about employment structure, workers' education and inequality in wage income are displayed in Sect. 10.4. Section 10.5 discusses and interprets in detail the empirical results obtained by estimating quantile regression equation. Section 10.6 summarises and concludes.

10.2 Data

National Sample Survey Office (NSSO) has been carrying out household-level survey on employment and unemployment situation in India roughly five years' interval

[3] Many countries in Asia, most notably India and China (PRC), are in a transition from planned economies to market-oriented economies. The structural transformation of the Indian economy from a socialistic to a pro-business path was well-underway before the 1991 reforms. China decided to liberalise its economy by the end of 1978 and towards the end of the 1980s, China entered into a new phase of reforms with a massive programme of rapid integration of its economy into the world economy, while India charted out its new course of development based on neo-liberal reforms in the early 1990s.

since the early 1970s (27th round survey). The survey data are available in digital form since 1983 (38th round survey). In this study, we have used this database from 38th, 50th, 61st and 68th round survey for the period 1983, 1993–94, 2004–05 and 2011–12, respectively. We have constructed a pooled sample of unit-level observations by using these four samples drawn independently from the same population at different points of time. The survey on employment and unemployment gathers information about wage income, household consumption, 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.

Wages are recorded in the survey valued at current prices on weekly basis which are used to analyse wage distribution and employment characteristics. The nominal wages at different survey rounds are converted into 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 65, the working age in the Indian labour market. Students and unpaid family workers have been excluded from the sample.

The activity status is classified into 13 groups consisting mainly different forms of self-employment, wage employment and other activities. Self-employed are those who operate their own farm or non-farm enterprises or are engaged independently in a profession or trade. The self-employed are further categorised into own-account workers, employers and unpaid workers in household enterprises. Wage employment is divided into regular wage employment and casual employment. Regular wage workers are those who work in other's farm or non-farm enterprises of household or non-household type and get salary or wages on a regular basis, not on the basis of daily or periodic renewal of work contract. This category not only includes persons getting time wage but also persons receiving piece wage or salary and paid apprentices, both full time and part-time. On the other hand, a person working in other's farm or non-farm enterprises, both household and non-household type, and getting wage according to the terms of the daily or periodic work contract is a casual wage labour. The survey data also provide the nature of job contract as no written job contract, written job contract for 1 year or less, written job contract for more than 1–3 years and written job contract for more than 3 years. By matching with type of job contract, it is observed that regular wage workers have written job contract for longer period while most of the casual workers have no written job contract at all. Thus, regular wage workers with job contract for longer years are treated as permanent workers and casual wage workers with no written job contract or job contract for very short period as temporary workers.

The structure of employment is different in the rural economy from that in the urban sector. In the rural economy, employment structure is classified broadly into farm and non-farm employment. Farm employment is further categorised into self-employment in agriculture (a major 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. The urban employment, on the other hand, is divided into self-employment, wage employment on regular basis and wage employment on casual basis.

10.3 Econometric Model

This study analyses the distribution of wage income in terms of human capital and employment characteristics of the working-age people by using quantile regression model. The wage equation is estimated at the selected quantiles of the wage distribution. The quantile regression model has been popularised after the publication of Koenker and Bassett (1978, 1982). The literature has been developed further by Machado and Mata (2005), Melly (2005), Firpo et al. (2009), Fortin et al. (2011), Lechmann and Schnabel (2012), Magnani and Zhu (2012), Chi and Li (2014). Quantile regression has been used in many empirical researches in analysing the distributional content of wage income because it has some advantages over the ordinary least square.[4] Quantile regression is more robust to non-normal errors and outliers. It allows to consider the impact of a covariate on the entire distribution of the dependent variable, daily wage in our model, not merely its conditional mean.

The basic model used in this study is described in short as follows:

We estimate the following wage regression equation:

$$lnw_i = \acute{X}_i \beta(\theta) + \varepsilon_i \tag{10.1}$$

here, w_i is wage earned by worker i, X_i is the vector of covariates including job types, education, experience, gender of worker i and so on, β is the coefficient vector, θ represents quantile of the wage distribution and ε_i is the idiosyncratic error.

The population conditional quantile distribution of (10.1), for all θ given the set of covariates X is

$$Q_\theta(lnw_i|X_i) = \acute{X}_i \beta(\theta), \tag{10.2}$$

Here, the underlying assumption is $Q_\theta(\varepsilon_i|X_i) = 0$ for all $\theta \in (0, 1)$.

Thus, Eq. (10.1) becomes

$$lnw_i = Q_\theta(lnw_i|X_i) + \varepsilon_i \tag{10.3}$$

Equation (10.3) states that the unconditional quantile wage is equal to its wage conditional on the vector of explanatory variables at the same quantile plus the random error.

The coefficient vector $\beta(\theta)$ at quantile θ can be estimated by minimising the following objective function (Koenker and Bassett 1978):

[4] For example, Poterba and Rueben (1995) and Mueller (2000) studied public–private wage differentials in the USA and Canada analysed the income and wealth distribution in the UK.

$$\hat{\beta}(\theta) = \underset{\beta}{argmin}\left[\frac{1}{n}\left(\sum_{i=1}^{n}\rho_\theta(lnw_i - X_i\beta)\right)\right] \quad (10.4)$$

Here, $\hat{\beta}(\theta)$ is called θ_{th} regression quantile, for any quantile $\theta \in (0, 1)$.

The objective function denotes the loss associated with the prediction errors. Quantile regression minimises a sum that gives asymmetric penalties $(1-\theta)|\varepsilon|$ for overprediction and $\theta|\varepsilon|$ for under prediction:

$$\rho_\theta(\varepsilon) = \theta\varepsilon, \text{ if } \in > 0$$

$$\rho_\theta(\varepsilon) = (\theta - 1)\varepsilon, \text{ if } \in < 0$$

Thus, the θ_{th} quantile regression estimators, $\hat{\beta}(\theta)$ are chosen by solving the following problem

$$\hat{\beta}^t(\theta) = \underset{\beta}{argmin}\left[\sum_{i\in\{i:lnw_i \geq X_i\beta\}}\theta|lnw_i - X_i\beta| + \sum_{i\in\{i:lnw_i < X_i\beta\}}(1-\theta)|lnw_i - X_i\beta|\right] \quad (10.5)$$

This non-differentiable function could be minimised by applying the simplex method. The median regression, least-absolute-deviations regression, is obtained by minimising

$$\hat{\beta}(0.5) = \sum_i |lnw_i - X_i\beta| \quad (10.6)$$

The median-regression line must pass through the pair of data points with half of the remaining data lying above the regression line and the other half falling below.

We have used bootstrap standard errors in estimating the conditional distribution of wages for given X_{i} and θ by applying the principle described in (10.4) or, (10.5):

$$\widehat{lnw_i} = \acute{X}_i\hat{\beta}(\theta) \quad (10.7)$$

The estimated coefficient vector measures the rates of return to the corresponding covariates at the selected quantile of the conditional wage distribution. Under some regularity conditions, the estimated conditional quantile function is a consistent estimator of the population conditional quantile function, uniformly in θ (Koenker and Bassett 1982; Hendricks and Koenker 1992).

10.4 Employment Structure and Inequality in Wage Income: Some Observed Facts

The broad structural characteristics together with economic and political institutions have an influence on employment and wage structure in the labour market, which in turn affect the distribution of wage income. The structural transformation in employment occurred in rural India from the farm to the non-farm sector, although very slowly. While agricultural households have been dominating in the rural economy, the share of employment in agriculture, both as self-employed and casual labour declined systematically since the early 1980s (Table 10.1). Increasing share in non-farm employment in the rural economy assumes significance in analysing the changing pattern of distribution in wage income. The scope of getting a job in the non-farm sector in rural India increased with growth and development and the observed statistics support this fact. The share of self-employment in non-agricultural activities increased till 2005 and stagnated thereafter, while casual workers in the non-farm sector increased significantly over the survey rounds.

The urban households are mostly engaged in non-farm employment in the form of self-employment followed by regular wage or salaried workers (Table 10.2). 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 information technology. The share of self-employment in urban households increased during 1993–2005, but declined thereafter. While the share of wage earners on regular basis declined during the early phase of new growth regime, it remained stagnant, and the share of casual workers increased during 2005–2012. Thus, the casualisation 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 10.1 Changes in employment structure in rural India

Employment type	Employment share			
	1983	1993–94	2004–05	2011–12
Self-employed in agriculture	55	47	44	41
Self-employed in non-agriculture	10	13	17	17
Regular wage earning				9
Casual labour in agriculture	25	24	22	17
Casual labour in non-agriculture	5	7	10	13
Others	5	9	8	3

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

Table 10.2 Changes in employment structure in urban India

Employment type	Employment share			
	1983*	1993–94	2004–05	2011–12
Self-employed	45	43	48	46
Regular wage earning	0	41	37	37
Casual labour	0	12	11	13
Others	55	4	3	4

Note *In 38th round survey household types are categorised into self-employment and other workers
Source As for Table 10.1

Around 30% of rural workers and 50% of urban workers were in wage employment, regular and casual basis taken together, in 2011–12 (Tables 10.1 and 10.2). Before estimating how returns to schooling affect the wage income at different locations of the wage distribution we have looked at how wage workers are distributed by their levels of education at each survey round and the estimated figures are shown in Table 10.3. The distributional pattern of wage workers in terms of their education has been changed in favour of the share of workers with higher education during the high growth regime in India. The share of workers in lower strata in terms of their education level declined while the share of those with higher levels of education increased significantly over time. The share of graduate and postgraduate workers increased spectacularly in 2011–12 as compared to the respective share in 1983. In 2011–12, around 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% had education-level graduate and above.

In 2011–12, 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 (Table 10.4). 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 at middle school or secondary level were mostly engaged in self-employment group either in the farm or non-farm

Table 10.3 Distribution of wage workers by levels of education in India (rural and urban)

Education level	1983	1993–94	2004–05	2011–12
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[a]	19.3[a]	25.3[a]
Graduate and above	4.5	9.5	13.4	17.6

Note [a]Includes both secondary and higher secondary levels
Source As for Table 10.1

sector. While the majority of the working-age people in the rural economy with higher level of education (higher secondary, diploma, graduate, postgraduate and above) absorbed as wage or salaried workers on regular basis in the non-farm sector, a notable share of them engaged as self-employed or family workers.

On the other hand, 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 (Table 10.5). More than one-fourth of the working people without any formal or informal education worked very indecent activities including begging as indicated by the category *other workers*. In the urban economy, roughly one-fifth of the working population 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-fourths of the urban working people who have education at postgraduation 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 and 70%, respectively. However, a significant part of the workers with higher level of education (higher secondary, diploma, graduate, postgraduate and above) were self-employed as own-account worker.

Therefore, accumulation of human capital through education is no longer a guarantee of getting better job with higher earning. Many socio-economic and cultural factors actually restrict the vulnerable people to enter into higher hierarchy employment. 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 as shown in Tables 10.4 and 10.5 for rural and urban areas respectively support indirectly these facts.

We have looked into the observed inequality in wage income keeping in mind the distribution of wage workers by their education and employment characteristics. Unequal access to education is one of the major causes of earning inequality. To understand how the incidence of inequality in wage income changes over time with levels of education we have estimated Gini index[5] of wage among workers by

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

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

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

Table 10.4 Distribution of educated working-age people by types of employment in rural India: 2011–12

Employment status	Education level									
	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 NSSO data

Table 10.5 Distribution of working-age people with different levels of education by employment type in urban India: 2011–12

Employment status	Education level									
	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

Source As for Table 10.4

Table 10.6 Gini index of weekly wages by workers' education

Education level	Survey years			
	1983	1993–94	2004–05	2011–12
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

Note Bold indicates estimate for all workers
Source As for Table 10.1

segregating wage workers by their education level (Table 10.6). Incidence of inequality is different among workers with different education. However, no specific pattern is observed between inequality and education. In 2011–12, wage inequality was the highest among workers with education at middle school level followed by primary or below primary level of education. Inequality in wage income among workers declined over the survey rounds, but the rate of decline over the last two survey rounds (2004–05 and 2011–12) was very slow. The rate of decline of wage inequality was different for different groups of workers by their education level. Inequality in wage income among workers with education-level graduate and above increased during the period between 2004–05 and 2011–12. The decomposition of Gini index suggests that inequality in wage income is driven mainly by 'between' group inequality. While overall inequality declined, 'between' group inequality increased during the high growth regime in the post-reform period. In 2011–12, about 56% of overall

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

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 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:

$$G = G_w + G_b + G_t$$

inequality was attributed to 'between' group inequality, where groups are formed by workers' education, while 10% was contributed by 'within-group' inequality.

10.5 Estimating Quantile Regression on Wage Income

To find out how wage income is affected by workers' education and employment status at different time points during the high growth regime, we have estimated conditional wage 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 (w). The predictors are the variables, both qualitative and quantitative that capture different dimensions of employment characteristics and education. The regression model at quantile θ shown in Eq. (10.1) is specified in expanded form as

$$w_i = \beta_0^\theta + \sum_j \beta_{1j}^\theta D_{i,\text{year}} + \beta_2^\theta D_{i,\text{F}} + \beta_3^\theta D_{i,\text{R}} + \sum_k \beta_{4k}^\theta D_{i,\text{edu}} + \beta_5^\theta D_{i,\text{TE}} + \beta_6^\theta \exp$$
$$+ \beta_7^\theta \exp^2 + \sum_l \beta_{8l}^\theta D_{i,\text{ES}} + \sum_{j,k} \gamma_{jk}^\theta D_{i,\text{year}} D_{i,\text{edu}} + \sum_{j,l} \delta_{jl}^\theta D_{i,\text{year}} D_{i,\text{ES}} + \varepsilon_i^\theta \tag{10.1'}$$

Here, D_{year} is a time dummy measuring the effect over time, D_{F} is a female dummy used for detecting gender gap in wage earnings, D_{R} is a dummy variable for capturing rural–urban differences, D_{ES} is used to capture earnings differences for workers with different employment statuses. Level of education, training and work experience are taken into the model to capture different dimensions of human capital. Education is taken as a categorical variable in terms of dummies (D_{edu}) based on different levels of education: below primary, primary, middle school, secondary, graduate and postgraduate. Work experience (exp) is calculated as workers' age less year of schooling. The squared term of experience is taken as one of the explanatory variables to examine the diminishing effect of experience on wage. The effects of vocational training and technical know-how on wages have been estimated by incorporating appropriate dummies (D_{TE}). We also incorporate interaction dummies to estimate the change in wage earnings over time for different types of workers and different education levels. Here, $0 < \theta < 1$ indicates the proportion of the population having scores below the quantile at θ. The ε^θ is independently and identically distributed random error.

The estimated results are shown in Table 10.7. 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 structure than other quantiles. The intercept term shows the real weekly wages at different percentiles of the sample in 1993–94 in the absence of effect of any predictor incorporated in the model. The real wage income at 90th percentile is more than 2.5 times the median wage income and more than 8.5 times the wage at the 10th percentile implying significant gap in wage income in the Indian labour market in the early 1990s. The three time dummies used in the model measure the time effect of wage income. The year 1993–94, just after the initiation of liberalising policy, is used as a reference period. 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, and at a higher rate at the upper end of the wage distribution.

The workers' schooling has favourable effect on wage income as expected. To estimate how workers' education has had impact on wage income, we have taken workers without any formal 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 10.7, wage income is increased with higher level of 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 only Rs. 151.63 at 10th percentile. The returns to education at every level increase as we move from lower to upper end of wage the distribution implying that education has positive impact on inequality. As returns to education have significant impact on wage income, the wage distribution became more unequal because of the difference in access to education. Gap in wage income across quantiles is relatively low at the below primary level and remarkably high at the graduate or postgraduate level of workers education. 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 but increased significantly at the upper percentiles over the period between 1993–94 and 2011–12. Thus, earnings inequality between different groups of workers even at the same level of education increased over time during the high growth regime.

Work experience has 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 are also high at the upper end of the wage distribution. A significant wage premium is observed for workers with technical education at every location of the wage distribution. The wage gap among workers because of the differences in technical know-how may be because of skill-biased technological change during the high growth phase in India.

To estimate the wage gap between workers in different employment statuses, we have taken *other* workers' group as the reference group. The estimated coefficients (β_8) suggest that workers in wage employment on regular basis are better off at every

Table 10.7 Quantile estimates of conditional earnings

Coefficients	Quantile level				
	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
β_0	50.89***	96.79***	173.67***	268.00***	442.55***
$\beta_{1,1983}$	−4.52	−9.35	−28.92	−51.08	−96.65*
$\beta_{1,2004}$	94.72***	154.69***	254.59***	588.66***	1238.74***
$\beta_{1,2011}$	181.75***	289.56***	425.79***	809.44***	1812.05***
β_2	−23.39***	−38.52***	−56.35***	−73.97***	−95.35***
β_3	−33.02***	−58.88***	−103.72***	−171.45***	−246.12***
$\beta_{4,\text{below primary}}$	9.56***	16.78***	31.37***	53.37***	66.56***
$\beta_{4,\text{primary}}$	13.07***	21.31***	43.42***	81.66***	108.41***
$\beta_{4,\text{middle school}}$	25.40***	46.39***	94.44***	193.72***	217.97***
$\beta_{4,\text{secondary}}$	70.61***	162.04***	349.28***	456.38***	521.93***
$\beta_{4,\text{graduate and above}}$	151.63***	530.15***	777.76***	1032.14***	1359.15***
β_5	60.24***	180.00***	330.61***	508.11***	749.15***
β_6	0.57***	1.11***	2.27***	4.53***	5.95***
β_7	−0.0001	−0.00001	−0.0001**	−0.00002*	−0.0001**
$\beta_{8,\text{regular wage}}$	80.85***	146.29***	222.94***	277.10***	299.61***
$\beta_{8,\text{casual wage}}$	40.60***	46.61***	34.01***	5.62	−45.63*
$\gamma_{1983,\text{graduate and above}}$	−105.38***	−480.50***	−553.98***	−588.59***	−734.27***
$\gamma_{2004,\text{graduate and above}}$	61.34***	46.94***	415.22***	636.05***	639.66***
$\gamma_{2011,\text{graduate and above}}$	90.08***	41.21***	689.69***	1151.88***	1024.16***
$\gamma_{1983,\text{secondary}}$	−43.52***	−133.61***	−261.74***	−244.97***	−241.62***
$\gamma_{2004,\text{secondary}}$	8.37*	−10.12	96.15***	382.63***	334.02***
$\gamma_{2011,\text{secondary}}$	17.65***	−28.24***	2.68	550.58***	404.77***
$\delta_{1983,\text{regular wage}}$	−94.29***	−163.48***	−208.40***	−258.57***	−282.29***
$\delta_{2004,\text{regular wage}}$	−78.58***	−153.93***	−276.34***	−493.69***	−825.58***
$\delta_{2011,\text{regular wage}}$	−94.36***	−185.47***	−325.71***	−537.30***	−852.34***
$\delta_{1983,\text{casual wage}}$	−22.80**	−30.78**	−24.19	−7.46	25.60
$\delta_{2004,\text{casual wage}}$	−78.67***	−130.68***	−220.22***	−534.27***	−1152.42***
$\delta_{2011,\text{casual wage}}$	−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% level, **significant at 5% level, the rest are statistically insignificant

Source Author's estimation with data from 38th, 50th, 61st and 68th rounds of NSSO by using STATA 15.1

location of the wage distribution and a greater extent at the top of the distribution. While the casual wage workers have got higher wages than the other workers up to 75th percentile level, they have earned lower wage at 90th percentile. Inequality in wage income is observed across different statuses of employment partly because of the differences in human capital. 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 at 90th percentile level. However, the wage gap between workers in different employment statuses has been declining over time during the high growth regime in India.

10.6 Conclusion

In this study, we have analysed how wage income has been changed with workers' education and employment structure over the new growth regime in India. The structural transformation in employment occurred in rural India from the farm to non-farm sector very slowly, and in the form of informal employment. 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 type of structural transformation of employment widens the wage gap between farm and non-farm sectors, and even between different segments within the non-farm sector in the economy.

The distributional pattern of wage workers in terms of their education has also been changed in favour of share of workers with higher education during the high growth regime in India. In 2011–12, while the majority of the working-age people in the rural economy with higher level of education absorbed as wage workers on regular basis in the non-farm sector, a notable share of them engaged as self-employed or family workers. In the urban economy, roughly one-fifth of the working population were absorbed in wage employment on casual basis in the private sector activities. Nearly, three-fourths of the urban working people who have education at postgraduation or above were mostly engaged in wage employment on a regular basis. Therefore, the accumulation of human capital through education is no longer a guarantee of getting a better job with higher earning.

Incidence of inequality is different among workers with different education. In 2011–12, wage inequality was the highest among workers with education at middle school level followed by primary or below primary level of education. Inequality in wage income among workers declined over the survey rounds, but inequality in wage income among workers with education level graduate and above increased during the period between 2004–05 and 2011–12. While overall inequality declined, 'between' group inequality increased during the high growth regime in India.

To find out how wage income is affected by workers' education and employment status at different time points during the high growth regime, we have estimated conditional wage earnings. The wage gap between workers at different percentiles increased over time during the high growth regime, and at a higher rate at the upper end of the wage distribution. The workers' schooling has a favourable effect on wage income as expected. Wage income is increased with a higher level of education at a higher proportional rate at higher percentiles in the wage distribution. As returns to education have significant impact on wage income, the wage distribution became more unequal because of the difference in access to education. The rural–urban earnings differential and gender gap in wage earnings are also high at the upper end of the wage distribution.

Workers in wage employment on regular basis are better off as compared to other workers at every location of the wage distribution and a greater extent at the top of the distribution. Inequality in wage income is observed across different statuses of employment partly because of the differences in human capital. 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.

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