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Research Article

Wage Gap and Employment Status in Indian Labour Market – Quantile Based Counterfactual Analysis

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This study examines the extent of wage gap between workers in permanent and temporary jobs but in roughly similar occupation types by evaluating the impact of workers' characteristics and education. The differential effects of the covariates on wage gap at different locations of the wage distribution are estimated by applying quantile regression model. After estimating the differential effects the relevance of glass ceiling or sticky floor hypothesis has been tested with Indian data. The wage gap between temporary and permanent employment is decomposed into endowment effect based on the difference in labour market characteristics and coefficient effect based on the difference in returns for the same characteristics. The study observes that the wage gap between temporary and permanent workers is wider at the upper tail of the distribution not rejecting the glass ceiling hypothesis. The decomposition analysis suggests that the wage gap presents in the Indian labour market primarily because of discrimination measured by the coefficients effects.

JEL codes: C21, D31, I24

Keywords: Employment Structure, Quantile Regression, Earnings Inequality, India

1 Introduction

Increasing earning inequality with a significant increase of temporary employment has been experiencing in almost all countries (both developed and developing) during the past three decades (Levy & Murmane, 1992; Juhn et al., 1993; Gottschalk & Smeeding, 1997; Banerjee & Piketty, 2005; Picchio, 2006; Naticchioni et al., 2008; Chancel & Piketty, 2017). But, the problem of inequality is more critical in the transitional developing economy, and the analysis of earning distribution with employment structure and other characteristics of the labour market assumes significance both in theoretical and empirical research. This study re-examines the wage gap between permanent and temporary workers engaged in roughly similar type of job by taking productivity enhancing factors like education, training and work experience into account in a transitional developing economy, India, after two and a half decades of economic reforms towards globalisation.

In India, employment has been generated mainly in the form of temporary employment of heterogeneous types during the high growth regime under economic liberalisation. This

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study analyses the driving forces behind the dynamics of wage gap with the latest round survey data on employment and unemployment conducted by the National Sample Survey Office (NSSO) in India. We define temporary employment in terms of job status and types of job contract. Casual workers with no written job contract or written job contract for very short period are treated as workers in temporary employment. Temporary workers do not enjoy social security benefits and they are getting wages according to the terms of the daily or periodic work contract. Temporary workers are casual workers and most of them have no written job contract, while permanent workers have written job contract for longer period. Permanent workers enjoy social security benefits and they get wage or salary payment on regular basis.

Workers' education and skill have normally been treated as the major factors determining the status of employment of a person. The human capital theory suggests that education and training would improve workers' skills, enabling them to work in the 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 & Addison, 1997). But, in a transitional developing economy like India, higher level of education does not provide any guarantee for high status employment. There are some other factors, mostly relating to gender, social, political and other characteristics of a person that may determine the job status and the respective pay structure in the labour market. This study estimates the relative contributions of these factors.

The return to education, the major determining factor of wage earning, may be different in different job status and at different locations of the distribution irrespective of gender and other characteristics of workers. Many empirical studies revealed that the return to education is higher at the top of the wage distribution than the return at the bottom of the distribution (González & Miles, 2001; Skyt Nielsen & Rosholm, 2001). There are some studies exploring wage gap between permanent and temporary workers after controlling the effects of education and other characteristics with data from European countries (for example, Picchio (2006); Naticchioni et al. (2008)), but no attempt has been made on the similar issue with Indian data. This study is an attempt to fill this gap in the literature.

We re-examine the nature of wage gap across different locations of wage distribution and look into the role of productivity enhancing characteristics like workers' education and training in determining the gap. The basic research question is to examine how much the wage gap varies at different locations of the wage distribution by evaluating the impact of workers' characteristics and education. To find out the differential effects of the covariates on wage at different locations of the wage distribution we have applied the quantile regression model. To examine the wage gap between workers in temporary and permanent employment across wage profile, and to test the relevance of *glass ceiling* or *sticky floor* hypothesis[1] we have followed Machado and Mata (2005) as suggested in Melly (2005). The wage gap between temporary and permanent employment is decomposed into endowment effect based on the difference in labour market characteristics and coefficient effect based on the difference in returns for the same characteristics.

[1] The *glass ceiling* effect refers to a wider wage gap at the top of distribution, suggesting that temporary in the high-income jobs are paid less than their permanent counterparts. The *sticky floor* appears when the gap widens at the bottom of the wage distribution.

The study observes that the wage gap between temporary and permanent workers is wider in the upper tail of distribution supporting the *glass ceiling* hypothesis. The decomposition analysis suggests that the pay gap presents in the Indian labour market primarily because of discrimination measured by the coefficients effects. The rest of the study is organised as follows. Section 2 describes, in short, the data used in this study. Section 3 describes the relevant summary statistics based on the 68^{th} round survey during 2011-12, the latest survey round in India, relating to employment structure and wage earnings. Section 4 deals with econometric methodology used in this study. Section 5 interprets the empirical results on the basis of econometric model described in section 4. Section 6 summarises and concludes.

2 Data

We have used unit level data from 68th rounds survey on employment and unemployment situation in India (Schedule 10) for the period 2011-12 provided by the NSSO. In schedule 10 of the survey round, 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 year to 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.

Wages are recorded in the survey both in cash and kind form valued at current prices on weekly basis. We have calculated daily wage from weekly wage total (cash and kind together) earned by a person by taking into account the person's work intensity in a week. Wage gap is estimated in this study on the basis of daily wages earned by the worker. Although there is no hard evidence that the rich are indeed being undercounted in employment and unemployment survey in India, there may be strong reasons to suspect the under-representation of the elite in the survey rounds. Thus, wage gap measured with employment and unemployment survey data underestimates the actual wage gap in the Indian labour market. We restrict the sample to persons aged between 15 and 65, the working age in the Indian labour market.

3 Descriptive Statistics

3.1 Labour market outcomes by level of education

Labour market outcomes in terms of nature of employment and occupation dependent highly on workers' education and other characteristics. Accumulation of human capital through education, however, is no longer a guarantee of getting better job with higher earning. Many socio-economic and cultural factors restrict the higher educated people to enter into higher hierarchy employment. In this section we have described the labour market outcomes at different levels of education on the basis of available information in the survey data. Wage workers (both permanent and temporary) are engaged in different types of jobs or occupation. In NSSO unit level data, workers' occupation is classified by national classification of occupation (NCO)[2]. We have constructed the distributions of wage workers separately for permanent and temporary types[3] by occupations as defined in one digit NCO (2004) at different levels of education with the latest available survey round (NSSO 68^{th} round in 2011-12) and are shown in Tables 1 and 2 respectively.

Table 1: Distribution of wage worker in permanent employment with different level of education by occupation type: 2011-12

Education Job type	Up to primary	Middle school	Secondary	Higher secondary	Graduate	Post graduate+
NCO: 1	2.7	3.2	4.3	5.2	10.2	14.6
NCO: 2	1.7	1.9	3.9	7.2	23.4	42.4
NCO: 3	2.6	5.3	12.9	24.6	28.7	23.1
Higher hierarchy jobs	**7**	**10.4**	**21.1**	**37**	**62.4**	**80**
NCO: 4	1.9	4.4	11	16.2	14.2	8.3
NCO: 5	16.9	23.3	21.8	19.2	7.8	4.2
Middle hierarchy jobs	**18.8**	**27.7**	**32.8**	**35.4**	**22**	**12.6**
NCO: 6	3.5	4.5	3.8	4.4	3.1	3.7
NCO: 7	19.5	17.3	14.7	8.8	6.4	1.6
NCO: 8	20.8	22.9	16.3	8.7	4.5	1.5
Low hierarchy jobs	**43.8**	**44.7**	**34.8**	**21.9**	**14**	**6.8**
NCO: 9	30.4	17.3	11.2	5.7	1.7	0.6

Note: **Higher hierarchy jobs** include NCO 1 (Legislatures and executives), NCO 2 (Professionals), and NCO 3 (Technicians & associate professionals); **Middle hierarchy jobs** include NCO 4 (Clerks) and NCO 5 (Service workers and shop and market sales workers); **Low hierarchy jobs** include NCO 6 (Skilled agricultural and fishery workers), NCO 7 (Craft and related trades workers), and NCO 8 (Plant and machinery operators and assemblers); and NCO 9 includes elementary occupations.
Source: Author's calculation with 68^{th} round unit level NSSO data

[2] In one digit classification, NCO (2004) describes the following occupations. NCO 1: Legislatures, executives, NCO 2: Professionals, NCO 3: Technicians & associate professionals, NCO 4: Clerks, NCO 5: Service workers and shop and market sales workers, NCO 6: Skilled agricultural and fishery workers, NCO 7: Craft and related trades workers, NCO 8: Plant and machinery operators and assemblers, and NCO 9: Elementary occupations

[3] Workers getting wages on regular basis with written job contracts for more than three years are treated as permanent workers. Casual wage workers with written job contract for very short period (less than three years) or no written job contracts are treated as temporary workers.

Distribution of workers in permanent employment by types of occupations at a particular level of education is not similar to that of the temporary workers. The proportion of higher hierarchy jobs (legislatures, executives, professionals and associate professionals) increases with the increase in education both in permanent and temporary employment, but in the case of temporary employment the relationship is not so strong. The incidence of higher hierarchy jobs is higher in permanent employment than in temporary employment with same level of education. For example, about 80 per cent of post-graduate workers in permanent employment are engaged in high hierarchy jobs, while the respective share in temporary employment is just above 20 per cent. Middle hierarchy jobs (clerks and service workers in sales) in permanent employment are concentrated among workers with secondary and higher secondary levels of education. But, the similar kind of jobs in temporary employment are centred at education level higher secondary and graduate. The incidence of low hierarchy jobs (skilled agricultural workers, crafts and related trades workers, and machinery operators) is high among permanent workers at education up to secondary level, but it is notably high at any education level among temporary workers. Around 41 per cent of the graduate and 29 per cent of the post-graduate workers in temporary employment are in low hierarchy jobs.

Table 2: Distribution of wage worker in temporary employment with different level of education by occupation type: 2011-12

Education Job type	Up to primary	Middle school	Secondary	Higher secondary	Graduate	Post graduate+
NCO:1	1.4	2.4	3	2.7	3.6	16.7
NCO:2	0.5	0.6	1	2	3.3	4.2
NCO:3	0.5	1.2	1.4	2.8	7.9	0
Higher hierarchy jobs	**2.4**	**4.1**	**5.4**	**7.6**	**14.8**	**20.8**
NCO:4	0.3	0.6	1.1	1.1	4.2	4.2
NCO:5	3.3	5.4	7.2	9.2	8.2	0
Middle hierarchy jobs	**3.6**	**5.9**	**8.4**	**10.3**	**12.4**	**4.2**
NCO:6	3.3	5.6	6.2	7.9	6.7	8.3
NCO:7	23.7	28	29.1	23.2	29.1	16.7
NCO:8	4.5	6.6	6.9	6.9	5.8	4.2
Low hierarchy jobs	**31.5**	**40.3**	**42.2**	**37.9**	**41.5**	**29.2**
NCO:9	62.5	49.7	44	44.2	31.2	45.8

Note: **Higher hierarchy jobs** include NCO 1 (Legislatures and executives), NCO 2 (Professionals), and NCO 3 (Technicians & associate professionals); **Middle hierarchy jobs** include NCO 4 (Clerks) and NCO 5 (Service workers and shop and market sales workers); **Low hierarchy jobs** include NCO 6 (Skilled agricultural and fishery workers), NCO 7 (Craft and related trades workers), and NCO 8 (Plant and machinery operators and assemblers); and NCO 9 includes elementary occupations.
Source: Author's calculation with 68^{th} round unit level NSSO data

A large part of the permanent workers with schooling up to primary level of education are in elementary occupation and in plant or machine operation (Table 1). Majority of such workers with middle school level of education work as sales person in shops and market places. While one-fourth of the permanent workers with education at higher secondary level are engaged in technical jobs, many of them were in sales service and clerical services. Workers in permanent employment who have graduation degree engage mostly as technicians, professionals, or clerks. All permanent workers with highest education are not in high profile occupations like executives, professionals or associate professionals. A noticeable part of them are in clerical jobs, or in sales services, or even in agricultural activities. The incidence of better quality jobs increases with the increase in education level in permanent employment, but the changing pattern of jobs with education is not systematic. Temporary workers, on the other hand, are concentrated mainly in low profile jobs and majority of them are in elementary occupation irrespective of their level of education (Table 2). Major part (62.5 per cent) of the wage workers with education up to primary level who are in temporary employment are absorbed in elementary occupation. Surprisingly enough, nearly 46 per cent of the post-graduates and 31 per cent of the graduates in temporary jobs are forced to accept elementary occupation in the Indian labour market.

3.2 Observed wage gap between permanent and temporary employment

The difference in labour market outcomes in the form of occupational and employment status between permanent and temporary workers has serious implications in explaining wage distribution of these two types of workers. Before analysing wage distribution in terms of workers' education and employment characteristics we have looked at the observed wage at different locations of the wage distribution. Daily wages for permanent and temporary workers at percentiles 10, 25, 50, 75 and 90 of the wage distribution have been estimated on the basis of sample observations taken from 68^{th} round survey by using appropriate sample weights obtained from the multiplier provided in the data to make estimates population representative. The estimated values are shown in Table 3.

Table 3: Wages in temporary and permanent employment at different locations of wage distribution: 2011-12

Location of wage distribution	Daily wage (Rs.)	
	Permanent worker	Temporary worker
Q10	100	80
Q25	150	100
Q50	300	150
Q75	643	200
Q90	967	250
Q90 / Q10	9.7	3.1
Mean	397	141
Standard error	4.03	0.67

Source: Author's calculation with 68^{th} round unit level NSSO data

Wage gap between workers in permanent and temporary employment presents at every location of the wage distribution and the extent of the gap becomes wider as we move from bottom end to top end of the distribution. At the middle point of the distribution, wage per working day of a person in permanent employment is double the wage of a person in temporary employment, while at the upper end (90^{th} percentile), the wage in permanent employment is roughly 4 times more than the wage in temporary employment. Thus, a higher wage differential between temporary and permanent employment is observed at the upper tail of the distribution implying the presence of *glass ceiling* effect in Indian labour market. The mean wage of the permanent workers is more than 2.5 times the mean wage of temporary workers. The extent of wage inequality (in terms of the ratio of 90^{th} percentile to 10^{th} percentile) among permanent workers is extremely high as compared to the wage inequality among temporary workers. The estimated standard errors of daily wages of these two groups also suggest the similar phenomenon.

The Kernel density estimates across the employment groups provide a better idea about the existing wage gap between workers in permanent and temporary employment. The density functions of daily wages for workers in temporary and permanent employment have been estimated by using an Epanechinov kernel estimator. As is shown by the shape of the estimated Kernel density function of log values of daily wages (Figure 1), the distribution of wage in permanent employment is significantly different from the wage distribution in temporary employment. The estimates reveal a larger proportion of the permanent workers to be in the higher wage levels. The two-sample Kolmogorov-Smirnov test is used to compare the observed cumulative distribution function for log values of daily wages with the normal distribution. The Kolmogorov-Smirnov Z-statistic is computed from the largest difference between the empirical and theoretical cumulative distribution functions. The test rejects the null hypothesis that the wages of the permanent and the temporary workers follow the same distribution at less than 1 per cent level of significance ($p - value = 0.001$).

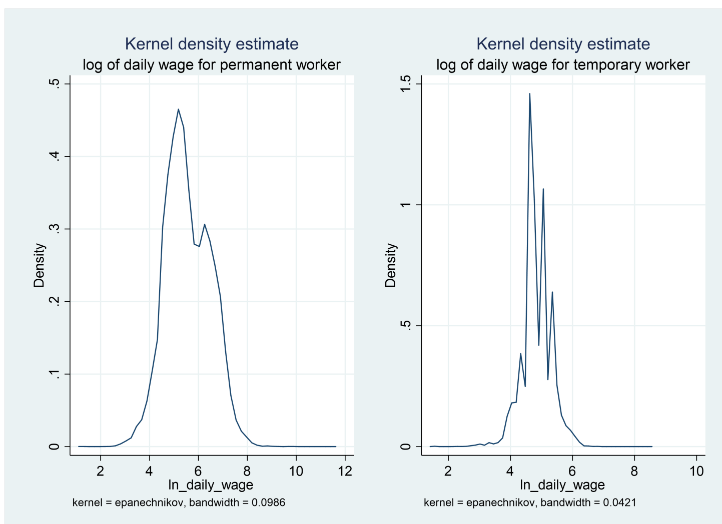

Figure 1: Kernel density function of log of daily wage

The extent of wage gap at different locations of wage distribution (as shown in Table 3) may be because of the differences in return to education in different status of employment. We have calculated average daily wage and Gini index of wages at different level of workers' education and in different types of job separately for permanent and temporary workers, and the results are displayed in Tables 4 and 5 respectively. Average wage increases significantly with education in permanent employment, while in temporary employment there is no such type of positive relationship between wage and workers' education (Table 4). As a result, wage gap between two types of employment increases with the level of workers' education. Similarly, the average daily wage increases with job hierarchy in permanent employment, but no such type of relationship observed in temporary employment. Thus, wage gap is extremely high in higher hierarchy jobs as compared to the gap in elementary occupations (Table 5).

Table 4: Average wage and Gini index of daily wage of permanent and temporary workers across education level: 2011-12

Education level	Permanent worker		Temporary worker	
	Average daily wage (Rs.)	Gini index	Average daily wage (Rs.)	Gini index
Not literate	163	0.38	128	0.23
Below primary	204	0.36	125	0.22
Primary level	192	0.37	146	0.25
Middle school level	221	0.38	156	0.28
Secondary level	305	0.4	159	0.26
Higher secondary	369	0.41	151	0.26
Diploma	486	0.37	222	0.31
Graduate	634	0.42	176	0.27
Post-graduate and above	840	0.4	151	0.21
All	397	0.49	141	0.25

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

The extent of wage inequality is not the same in permanent and temporary employment, and it varies across workers' education level and job types. Wage distribution in permanent employment is more unequal than in temporary employment, and the incidence of inequality is different at different level of workers' education as well as in different types of jobs. The relationship between wage inequality and workers' education is different in permanent employment from that in temporary employment. In permanent employment, the incidence of wage inequality is the highest among graduate workers and the lowest among workers with education below primary level. In temporary employment, on the other hand, the extent of wage inequality is the highest among diploma holders and the lowest among post-graduate workers. However, there is no specific pattern of relationship between wage inequality and job hierarchy is observed both in permanent and temporary employment. Gini index of daily wages is the maximum in the top ranking jobs followed by services workers and trade workers in permanent employment. In temporary employment, on the other hand, Gini index is the highest among technicians and the lowest in elementary occupations.

Table 5: Average wage and Gini index of daily wage of permanent and temporary workers across education level: 2011-12

Job types	Permanent worker		Temporary worker	
	Average daily wage (Rs.)	Gini index	Average daily wage (Rs.)	Gini index
Legislatures and executives	795	0.51	132	0.3
Professionals	775	0.4	139	0.29
Technicians	539	0.39	148	0.33
Clerks	465	0.36	151	0.27
Service workers	288	0.42	149	0.31
Skilled agricultural workers	200	0.4	134	0.26
Craft and related trades workers	267	0.42	174	0.28
Plant and machinery operators	266	0.36	175	0.28
Elementary occupations	185	0.4	132	0.23
All	397	0.49	141	0.25

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

4 Econometric model

This paper analyses wage gap (as shown in Tables 3 to 5) between permanent and temporary employment in the Indian labour market in two steps. In the first step, the wage equation is estimated at the selected quantiles of the wage distribution. In the second step, wage gaps at the selected quantiles are estimated and decomposed into endowment effects originated from the difference in the productive characteristics of the workers, and differential returns effects initiated from the differences in returns to the productive characteristics following quantile decomposition method. This method enables us to explore the potential effects on the shape of the distribution in addition to the shift of the distribution due to the shift of the covariates. 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) along with other scholars to apply quantile regression in decomposition analysis of wage distribution. Quantile regression has been used in many empirical research relating to labour market discrimination 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.

In quantile regression framework we estimate the following wage regression equation:

$$lnw_i \ = \ \acute{X}_i\beta(\theta) \ + \ \epsilon_i \tag{1}$$

Here, w_i is daily wage of worker i, X_i is the vector of covariates including job types, education, experience, and gender of worker i, 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 (1), for all θ given the set of covariates X is

$$Q_\theta(lnw_i|X_i) = \ \acute{X}_i\beta(\theta) \tag{2}$$

Here, the underlying assumption is $Q_\theta(\epsilon_i|X_i) = 0 \ \forall \ \theta \in (0,1)$. Thus, equation (1) becomes

$$lnw_i \ = \ Q_\theta(lnw_i|X_i) \ + \ \epsilon_i \tag{3}$$

Equation (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 & Bassett, 1978):

$$\hat{\beta}(\theta) \ = \ \underset{\beta}{\operatorname{argmin}} \left[\frac{1}{n} \left(\sum_{i=1}^{n} \ \rho_\theta(lnw_i \ - \ X_i\beta) \right) \right] \tag{4}$$

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

[4] For example, Poterba and Rueben (1994) and Mueller (2000) studied public-private wage differentials in the United States and Canada analysed the income and wealth distribution in the United Kingdom.

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

$$\rho_\theta(\epsilon) \;=\begin{cases} \theta\epsilon \quad , & \text{if } \epsilon > 0. \\ (\theta-1)\epsilon, & \text{if } \epsilon < 0. \end{cases}$$

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

$$\hat{\beta}^t(\theta) = \underset{\beta}{\operatorname{argmin}} \left[\sum_{i \in \{i: lnw_i \geq X_i\beta\}} \theta|lnw_i - X_i\beta| \;+ \sum_{i \in \{i: lnw_i < X_i\beta\}} (1-\theta)|lnw_i - X_i\beta| \right] \quad (5)$$

This non-differentiable function could be minimised by applying the simplex method.

The median regression, least-absolute-deviations regression, is obtained by minimising

$$\hat{\beta}(0.5) \;=\; \sum_i |lnw_i \;-\; X_i\beta| \quad (6)$$

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 (4) or, (5):

$$\widehat{lnw_i} \;=\; \acute{X}_i\hat{\beta}(\theta) \quad (7)$$

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 & Bassett, 1978; Hendricks & Koenker, 1992).

After estimating the model given in (1) we decompose the wage differences at selected quantiles of the wage distribution between workers in permanent and temporary jobs into the component due to labour market characteristics and the component due to the differences in returns by following Melly (2005). This method is an extension to the counterfactual wage decomposition approach of Oaxaca (1973) to quantile regression and provides a general strategy for simulating marginal distributions from the quantile regression process. The Oaxaca decomposition fails to provide information about the whole distribution (Magnani & Zhu, 2012; Chi & Li, 2014; Ahmed & McGillivray, 2015). Machado and Mata (2005) proposed a quantile-based decomposition method, which combines quantile regression with bootstrap approach. Melly (2005) modified the methodology developed in Machado and Mata (2005) by decomposing the wage differences at different quantiles of the unconditional distribution.

In this study, workers in permanent employment is treated as population group θ and those in temporary employment as population group 1. Let F_{X_k} (X) and $F_{W_j}(W|X)$ be the distributions of workers' characteristics X and wage W conditional on X respectively in $k \in (0,1)$ and $j \in (0,1)$. We estimate the conditional distribution by using quantile regression model.

The unconditional wage distributions of workers in permanent and temporary employment are obtained from the estimated conditional distribution in the following way:

$$F_{W\langle 0|0\rangle}(W) \;=\; \int F_{W_0}(W|X)\; dF_{X_0}(X) \tag{8}$$

$$F_{W\langle 1|1\rangle}(W) \;=\; \int F_{W_1}(W|X)\; dF_{X_1}(X) \tag{9}$$

Let we define

$$F_{W\langle j|k\rangle}(W) \;=\; \int F_{W_j}(W|X)\; dF_{X_k}(X) \tag{10}$$

as the counterfactual distribution of wages of workers' group j if they have the characteristics of workers' group k[5]. Therefore, the counterfactual wage distribution of workers in permanent employment is

$$F_{W\langle 0|1\rangle}(W) \;=\; \int F_{W_0}(W|X)\; dF_{X_1}(X) \tag{11}$$

This distribution is constructed by integrating the conditional distribution of wages for workers in permanent employment with respect to the distribution of characteristics of those in temporary employment. The counterfactual distribution is estimated by using the unconditional distribution, and by replacing the estimated parameters of the distribution or the characteristics of permanent workers with those of temporary workers.

We define the distributional effect on wages between these two groups of workers as

$$D(W) \;=\; F_{W\langle 0|1\rangle}(W) \;-\; F_{W\langle 0|0\rangle}(W) \tag{12}$$

The quantile measure of the distributional effect[6] shown in (12) is

$$Q(\theta) \;=\; Q_{W\langle 0|1\rangle}(Q) \;-\; Q_{W\langle 0|0\rangle}(Q) \tag{13}$$

If workers in temporary employment are in treatment group (1) and workers in permanent employment are in control group (0), the quantile treatment effect on the treated is obtained from the counterfactual distributions as

$$QTET \;=\; Q_{W\langle 1|1\rangle}(Q) \;-\; Q_{W\langle 0|1\rangle}(Q) \tag{14}$$

[5] As this distribution is not derived from any observable population, it is called counterfactual distribution.
[6] The quantile wage function, the inverse of the wage distribution function, $F_W^{-1}(\theta)$, evaluated at θ, $0 < \theta < 1$ is defined as

$$Q_{W_{\langle j|k\rangle}}(\theta) \;=\; inf\{W : F_{W_{\langle j|k\rangle}}(W) \geq \theta\},\; 0 < \theta < 1$$

Theoretically, it is easy to estimate the conditional distribution function by inverting the conditional quantile function. However, the estimated conditional quantile function is not necessarily monotonic and thus cannot be simply inverted.

Therefore, the quantile decomposition,

$$
\begin{aligned}
Q_{W\langle 0|0\rangle}(Q) \; - \; Q_{W\langle 1|1\rangle}(Q) \;=\; & \big(Q_{W\langle 0|0\rangle}(W) \; - \; Q_{W\langle 0|1\rangle}(W)\big) \; + \\
& \big(Q_{W\langle 0|1\rangle}(W) \; - \; Q_{W\langle 1|1\rangle}(W)\big)
\end{aligned}
\tag{15}
$$

Or,

$$
\begin{aligned}
Q(X_{i,0}, \beta_0, \theta) \; - \; Q(X_{i,1}, \beta_1, \theta) \;=\; & \big[Q_{\theta(X_0, \beta_{0,\theta})} - Q_{\theta(X_1, \beta_{0,\theta})}\big] \; + \\
& \big[Q_{\theta(X_1, \beta_{0,\theta})} - Q_{\theta(X_1, \beta_{1,\theta})}\big]
\end{aligned}
\tag{16}
$$

The first component of wage penalty measures the wage gap because of the differences in workers' characteristics and the second component measures the difference in the returns given their job characteristics between workers in temporary and permanent employment.

5 Empirical results

5.1 Estimation of quantile regression

It is clear from the descriptive statistics as shown in section 3 that the wage gap between permanent and temporary employment depends partly on the differences in labour market characteristics like workers' education and occupation. This section analyses the estimated wage penalty of the temporary workers at different locations of the wage distribution. To find out how workers' education and other characteristics contribute to wage penalty to temporary workers, the wage regression is estimated 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}. We have taken log values of daily wages as dependent variable and variables relating to human capital, employment, industry, and region along with gender and person specific other factors like ethnic characters as covariates.

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 based on different levels of education: below primary, primary, middle school, secondary, graduate and post-graduate. Work experience 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 daily wages have been estimated by incorporating appropriate dummies. Gender, and ethnic status of workers are taken as person specific control variables to analyse the differential effects of education and training on daily wages. India is geographically very large country with heterogeneous regions and the regional effects of wage differential are measured by introducing region dummies. The variation of daily wages across industries after controlling the effects of human capital and job market characteristics is measured by the coefficients of industry dummies constructed on the basis of one digit industrial classification code (NIC 2008). The dummy variable for workers in permanent employment identified by their principal job status and type of job contracts is used to measure the extent to which wage gap between the two groups of workers remains unexplained at each quantiles after controlling for human capital and job characteristics. The variation of wage gap across gender, region and job types are captured by interaction dummies. The difference in return to education is estimated by the coefficient of interaction of dummy for permanent workers and year of schooling.

The estimated results based on quantile regression model of the wage distribution are shown in Table 6. The intercept term shows the conditional log wage for workers at different quantiles of the wage distribution in the sample irrespective of their level of education, job contracts, payment types and other characteristics of the workers. A huge difference in wage between upper quantile and lower quantile is observed. While workers in temporary employment enjoy wage premium up to median level, a significant wage penalty for them is observed at the top of the distribution. The estimated coefficients of the dummy variable for permanent workers (D_permanent) at different quantiles reject the hypothesis of *sticky floor*s. As revealed by the negative coefficients of gender dummy (D_female), women workers have earned lower wage than the men workers and the gender gap is more at the lower tail of the distribution.

The level of education has favourable effect on wage income as expected. To estimate how workers' education has had impact on wage earnings we have taken workers without any formal education as a reference group and compare wage earnings across workers with different levels of education by incorporating education dummies. As shown in Table 6, return to education increases with education level supporting the hypotheses put forward in the human capital theory, and the return to education at post graduate level is the highest at 25^{th} quantile of the wage distribution. The return to education at the upper tail is significantly higher than that at the lower tail of the wage distribution irrespective of the level of education. However, the effect of experience on wage is roughly similar across different location of the distribution. Wage premium for technical education is the highest at 90th quantile. The wage gap among workers because of the differences in technical know-how may be because of skill biased technological change during the post-liberalisation period.

Social status has a differential effect on wage. Workers in Scheduled Tribes (denoted by the dummy variable D_ST) earn more daily wage as compared to workers from upper caste at every location of the wage distribution and the gap is higher at the lower end. This is probably because the reservation policy of the government of India for them is helpful to get a job under ceteris paribus condition. Scheduled Castes people (D_SC), on the other hand, earn less wage than the people in general castes. To estimate regional variation of the wage gap at different quantiles we have constructed dummy variables for Northern, Southern, Eastern and Western regions of India and incorporate three dummies into the regression model by taking Western region as a reference category. Estimated coefficients of the dummies (D_region_north, D_region_south, D_region_east) reveal that persons in temporary employment working in Southern region states enjoy wage premium at the greatest extent compared to those working in Western part of the country at every location of wage distribution and the wage premium is higher at the upper end. For example, at 90^{th} quantile, the premium for workers in Southern states is 40 per cent while for those in Northern states is 28 per cent. However, the pay gap between Western and Eastern states is very low. The estimated coefficients of interaction between dummy for permanent workers and regional dummies clearly indicate the presence of wage premium for temporary workers in Southern region states and Northern states compared to the Western part of the country.

Table 6: Quantile estimates of conditional earnings

	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
Intercept	3.27***	3.45***	3.76***	4.04***	4.32***
D_permanent	-0.23***	-0.16***	-0.14***	0.03	0.32***
D_female	-0.38***	-0.36***	-0.38***	-0.36***	-0.33***
D_below_primary	0.07***	0.09***	0.10***	0.13***	0.16***
D_primary	0.08***	0.11***	0.13***	0.16***	0.20***
D_middle_school	0.12***	0.15***	0.19***	0.24***	0.26***
D_secondary	0.21***	0.24***	0.29***	0.35***	0.38***
D_higher_secondary	0.26***	0.33***	0.41***	0.43***	0.46***
D_graduate	0.45***	0.61***	0.57***	0.54***	0.59***
D_postgraduate	0.68***	0.83***	0.76***	0.71***	0.80***
experience	0.05***	0.05***	0.05***	0.04***	0.04***
exp2	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
D_vocational_training	-0.05***	-0.04***	-0.03***	-0.02***	-0.02*
D_technical_education	0.15***	0.15***	0.19***	0.22***	0.24***
D_ST	0.09***	0.07***	0.05***	0.04***	0.04***
D_SC	0	-0.01	-0.02**	-0.03***	-0.04***
D_region_north	0.24***	0.28***	0.27***	0.27***	0.28***
D_region_east	0.07***	0.11***	0.06***	0.05***	0.02
D_region_south	0.32***	0.37***	0.35***	0.38***	0.40***
D_high_skill	-0.32***	-0.24***	-0.14***	-0.03	0.24***
D_mid_skill	-0.27***	-0.23***	-0.19***	-0.10***	0.02
D_low_skill	0	0.02*	0.03***	0.06***	0.12***
D_permanent_education	0.04***	0.04***	0.04***	0.04***	0.03***
D_permanent_female	-0.26***	-0.28***	-0.06***	0.11***	0.15***
D_permanent_region_north	-0.21***	-0.16***	-0.14***	-0.14***	-0.16***
D_permanent_region_east	-0.01	0.02	0.07***	0.07***	0.07***
D_permanent_region_south	-0.18***	-0.26***	-0.32***	-0.39***	-0.41***
D_permanent_high_skill	0.49***	0.46***	0.48***	0.44***	0.16***
D_permanent_mid_skill	0.25***	0.26***	0.31***	0.27***	0.14***
D_permanent_low_skill	0.14***	0.11***	0.12***	0.10***	0.05***
D_industry1	-0.01	0.04**	0.07***	-0.01	-0.14***
D_industry2	0.23***	0.19***	0.19***	0.12***	0.03
D_industry3	0.23***	0.31***	0.47***	0.45***	0.29***
D_industry4	0.19***	0.16***	0.17***	0.16***	0.09***
D_industry5	0.20***	0.19***	0.22***	0.23***	0.13***
D_industry6	0.39***	0.42***	0.59***	0.56***	0.43***
D_industry7	0.32***	0.33***	0.42***	0.39***	0.33***
D_industry8	0.22***	0.38***	0.52***	0.41***	0.21***
D_industry9	-0.16***	-0.11***	-0.08***	-0.13***	-0.22***
Pseudo R2	0.194	0.243	0.339	0.43	0.41

Note: *** significant at less than 1 per cent level, ** significant at 5 per cent level, the rest are statistically insignificant. Industry dummies are constructed on the basis of one digit NIC 2008. Accordingly Industry0: Agriculture, mining and quarrying; Industry1: Manufacturing; Industry2: Electricity, gas; Industry3: Steam and air conditioning supply; Industry4: Water supply; sewerage, waste management and remediation activities; Industry5: Construction; Industry6: Wholesale and retail trade; repair of motor vehicles and motorcycles; transportation and storage; Industry7: Accommodation and food service activities; Industry8: Information and communication; financial and insurance activities; Industry9: Real estate activities; professional, scientific and technical activities; administrative and support service activities; public administration and defence; compulsory social security; education; human health and social work activities

Source: Author's estimation with unit level data from 68^{th} rounds of NSSO.

The extent of wage penalty among temporary workers is differentiated across job hierarchies. To estimate the differential effects we have used 3 dummies to represent high hierarchy jobs, middle hierarchy jobs and low hierarchy jobs (D_high_skill, D_mid_skill, and D_low_skill) based on workers' skill by taking elementary jobs as the reference group. High hierarchy jobs or, white collar jobs are skill intensive. The distribution of workers as shown in Tables 1 and 2 reveals that workers in this type of jobs are mostly permanent enjoying significant skill premium. Temporary workers with no sufficient skill in high hierarchy jobs earn less wages compared to wage earnings of similar type of workers in elementary employment, and the temporary-permanent wage gap is more prominent at median of the distribution. Industry specific fixed effects have also been incorporated in determining wage gap between temporary and permanent workers are estimated by using industry dummies taking agro-based industries as the reference industry group. Estimated coefficients of the dummies measure the unobserved heterogeneity across industry groups that have significant effect on wages.

5.2 Decomposition of wage gap

By following Melly (2005), wage gap between workers in permanent and temporary employment is decomposed into endowment and coefficient effects at selected locations of wage distribution in a quantile regression framework. The sample data used contain 66,204 wage workers among which 39,789 are in permanent employment and 26,415 are in temporary employment. To look into gender differences in wage gap we also decompose the raw difference separately for men and women workers. The estimated results shown in Table 7 highlight that workers in temporary employment roughly similar to those in permanent employment fall behind the latter more at the top of wage distribution.Wage gap presents and it increases monotonically towards the right tail of the distribution not rejecting the *glass ceiling* hypothesis. Wage penalty for temporary workers persists in Indian labour market primarily because of coefficients effect. However, at the lower end of the distribution, the major part of the wage difference could be explained by the differences in productive endowments between permanent and temporary workers. Raw wage difference between permanent and temporary workers among women is negative at 10^{th} quantile implying that women temporary workers earning very low wage enjoy wage premium.

Table 7: Machado-Mata decomposition of wage gap

All workers	Q_{10}	Q_{25}	Q_{50}	Q_{75}	Q_{90}
Raw difference	0.131	0.432	0.811	1.135	1.321
Characteristics	0.129	0.089	0.123	0.147	0.236
Coefficients	0.003	0.344	0.688	0.988	1.085
Women workers					
Raw difference	-0.159	0.136	0.687	1.319	1.618
Characteristics	0.141	0.118	0.162	0.291	0.573
Coefficients	-0.3	0.017	0.525	1.029	1.045
Men workers					
Raw difference	0.146	0.463	0.803	1.114	1.29
Characteristics	0.045	0.064	0.083	0.124	0.2
Coefficients	0.101	0.399	0.72	0.99	1.09

Source: Author's estimation with unit level data from 68th rounds of NSSO.

6 Summary and conclusions

In this study, we have analysed wage gap between workers in permanent and temporary employment in terms of workers' education and type of jobs. Worker's education is important in explaining employment characteristics as well as earnings inequality. The study observes that job distribution by education of permanent workers is not similar to that of the temporary workers. The proportion of higher hierarchy jobs is high among the permanent workers compared to the temporary workers. The incidence of low hierarchy jobs is high among permanent workers at education up to secondary level, but it is notably high at any education level among temporary workers.

Wage distribution in permanent employment is more unequal than in temporary employment, and the incidence of inequality is different at different level of workers' education as well as in different types of jobs. Wage gap presents at every location of the wage distribution and the extent of the gap becomes wider as we move from bottom end to top end of the distribution. Wage gap increases with the level of workers' education and it is extremely high in higher hierarchy jobs.

While workers in temporary employment enjoy wage premium up to median level, a significant wage penalty for them is observed at the top of the distribution rejecting the hypothesis of *sticky floor*s. Return to education increases with education level supporting the hypotheses put forward in the human capital theory. The return to education at the upper tail is significantly higher than that at the lower tail of the wage distribution irrespective of the level of education. The wage gap, as observed in this study, among workers because of the differences in technical know-how may be because of skill biased technological change during the post-liberalisation period.

Workers in Scheduled Tribes earn more daily wage as compared to workers from upper caste at every location of the wage distribution and the gap is higher at the lower end. Persons in temporary employment working in Southern region states enjoy wage premium at the greatest extent compared to those working in Western part of the country. However, the pay gap between Western and Eastern states is very low.

Temporary workers with no sufficient skill in high hierarchy jobs earn less wages compared to wage earnings of similar type of workers in elementary employment. Temporary workers with no sufficient skill in high hierarchy jobs earn less wages compared to wage earnings of similar type of workers in elementary employment. Wage gap for temporary workers persists in Indian labour market primarily because of coefficients effect. However, at the lower end of the distribution, the major part of the wage difference could be explained by the differences in productive endowments between permanent and temporary workers.

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