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RESEARCH NOTE

Gender Discrimination in Wage Earnings: A Study of Indian Wage Market

Mitali Chinara[1]

Abstract

The fact that globally a gender gap exists along axes of economic, social and political outcomes is well documented. Studies have shown such gaps to be increasing or decreasing, changing by varying degrees, varying by magnitude depending on the period of study and region of analysis. The World Economic Forum's Global Gender Gap Report shows tardy progress on closing the gender gaps along multiple axes. The report states that even while the global gender gap has become smaller since 2006, the extent of its closure is a measly four per cent; if this trend were allowed to perpetuate, it would take over a 100 years for the world's women to be on par with men. India has tightened its gender gap by 2% in a year, which now stands at 68% across the four pillars of economy, education, health and political representation. The major improvement, however, has been witnessed in the arena of education, where the gaps in primary and secondary education have been completely eliminated. In the economic sphere, much work remains to be done. In so far as ensuring gender equality continues to be one of the objectives of Sustainable Development Goals, lack of it constitutes a challenge. Such gap is, however, either on account of inputs or characteristics that are different across members of different genders (the explained gap) or on account of differential premium on possession of comparable characteristics across genders (the unexplained gap). Decomposition of such gaps into their explained and unexplained fractions is important for the purpose of measuring the precise extent of gender discrimination. This paper fills a void in the existing literature by analysing such gaps in the wage market across select states of India. The paper uses the technique of Blinder–Oaxaca decomposition for the purpose of study, which has not been applied so far in studying inter-state characterization of gender wage gaps. Thereafter, the paper compares the results obtained for pooled wage market of India with results for urban and rural wage markets.

Keywords Blinder–Oaxaca · Decomposition · Gender · Wage gap

✉ Mitali Chinara
mitalichinara@yahoo.co.in

[1] P G Department of Analytical and Applied Economics, Utkal University, Bhubaneswar, Odisha 751004, India

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1 Introduction

World Economic Forum's Global Gender Gap Report affords scope for analysing long-run trends in gender equality along indices of economic participation and opportunity, educational attainment, health and survival and political empowerment—using their attendant indicators. The 2016 report (WEF 2016) shows tardy progress on closing the gender gaps along multiple axes. The report states that even as the global gender gap has become smaller since 2006, the extent of its closure is a measly four per cent; if this trend were allowed to perpetuate, it would take over a 100 years for the world's women to be on par with men.

India is ranked 87 out of 144, improving from its 108 position in 2015. It has closed its gender gap by 2% in a year: its gap now stands at 68% across the four pillars of economy, education, health and political representation. The major improvement, however, has been in the arena of education, where the gaps in primary and secondary education have been completely eliminated. In the economic sphere, much work remains to be done. Overall, it ranks 136 in this pillar (of economic participation and opportunity) out of 144 countries, coming in at 135th for labour force participation and 137th for estimated earned income. India ranks 103 in terms of wage equality between men and women. Clearly, therefore, albeit India has improved its gender gap by 8%, much work remains to be done in terms of bridging the economic gap between men and women—particularly, in terms of the wage gap between the two genders.

The International Labour Organization's report—*Women at Work: Trend 2016* (ILO 2016)—finds that gender equality in work place remains elusive. As per the ILO, inequality between men and women can be observed in global labour markets, with respect to opportunities, treatment and outcomes. Since the Fourth World Conference on Women in Beijing in 1995, the improvements have been at best marginal, leaving large gaps to be covered in the implementation of the 2030 Agenda for Sustainable Development, adopted by the United Nations in 2015. Over the last two decades, there has been significant progress in educational achievements of women, but these have not manifested in substantial improvement in their positions at avenues of employment. In numerous regions in the globe, in comparison with their male counterparts, females have higher propensity of becoming and remaining unemployed, have lower probabilities of participating in the labour force and—when they occasionally do—are often at a qualitative disadvantage in terms of job profile. Worldwide, the chances for women to participate in the labour market remain almost 27% lower. Substantial cohorts of women worldwide are deprived of same kind of sought-after, high-salary jobs as men. New data from 178 countries paints a bleak portrait of the status of contemporary working women. As per the report, the gender gaps in employment, wages and social protection have altered preciously little in 20 years and that women are less likely to participate in the labour market than men. As stated by Deputy Director of ILO Lawrence Johnson, 'At the global level, the employment gender gap has closed only by 0.6 percent between 1995 and 2015.

This means progress in getting women into more jobs is either insufficient or has flat-lined.'

Persistently during the duration of their working lives, women still face significant obstacles in gaining access to decent jobs. Success in overcoming such barriers has not just been tardy in pace, but what is more important, has been restricted to a few pockets across the globe. The quality of women's jobs is a cause of concern even in countries at the forefront of gender parity, i.e. where gaps in labour force participation rates and employment along the gender axis have narrowed and women are transitioning from contributing to family work to being absorbed in the services sector. Globally, the wage gap between males and females is estimated to be 23%; in plain speak, women earn 77% of what men earn, and these gaps cannot be explained by differences in labour market characteristics such as education, training or experience. As maintained before, improvements have been rather insignificant, slow and profoundly localized. It has been estimated that going by the prevailing trends, the gender gaps will take over 70 years to entirely close themselves. Another worrying finding of the ILO report has been that the gender wage gaps are uncorrelated with a country's level of economic development—some countries with high per capita income levels exhibit high gender wage gaps.

The 2012 World Bank Report emphatically proclaimed that engendering gender equality is characteristically 'Smart Economics', with salubrious significant effects on economic productivity, development outcomes for the next generation and representativeness of institutions and policies (and so laws and policies become more efficacious for all the diverse groups of society, more pronouncedly for the marginalized). Hence closing the gender gaps is a desirable objective for economies at all levels of development.

This paper intends to use the widely used Oaxaca-Blinder decomposition technique to investigate the level of gender gap in wage earnings across India, using the NSS 66th round data findings. Thereafter, this gender gap in wages will be compared with the gaps in rural and urban wage markets of the country, to get a holistic understanding of the wage gap across axis of gender across states of India.

2 Methodology

An often used methodology to study labour market outcomes by groups (sex, race, and so on) is to decompose mean differences in log wages based on regression models in a counterfactual manner. The procedure is known in the literature as the Blinder–Oaxaca decomposition (Blinder 1973; Oaxaca 1973) and divides the wage differential between two groups into a part that is 'explained' by group differences in productivity characteristics such as education, training or work experience and a residual part that cannot be accounted for by such differences in wage determinants. This 'unexplained' part is often used as a measure for discrimination, but it also subsumes the effects of group differences in unobserved predictors. Most applications of the technique can be found in the labour market and discrimination literature. A brief explanation of the technique is in order, before it is applied for the purposes of analysis. This section draws on the exposition in Jann 2008.

Given are two groups A and B, an outcome variable Y, and a set of predictors. In our case, groups refer to males and females, suppose (log) wages be the outcome variable, and human capital indicators such as education and work experience be predictors. The question now is how much of the mean outcome difference

$$R = E(Y_A) - E(Y_B) \tag{1}$$

where $E(Y)$ denotes the expected value of the outcome variable, is accounted for by group differences in the predictors.

Based on the linear model

$$Y_W = X'_W \beta_W + \varepsilon_W, \quad E(\varepsilon) = 0, \quad W \in \{A, B\} \tag{2}$$

where X is a vector containing the predictors and a constant, β contains the slope parameters and the intercept, and ϵ is the error, the mean outcome difference can be expressed as the difference in the linear prediction at the group-specific means of the regressors. That is

$$R = E(Y_A) - E(Y_B) = E(X_A)'\beta_A - E(X_B)'\beta_B \tag{3}$$

since $E(Y_W) = E(X'_W\beta_W + \varepsilon_W) = E(X'_W\beta_W) + (\varepsilon_W) = E(X'_W)\beta_W$ with $E(\beta_W) = \beta_W$ and $E(\varepsilon_W) = 0$ by assumption.

In the above formulation, the slope coefficients—sometimes referred to alternatively as 'rates of return' to a predictor—vary as per the group being considered. This difference in the slope coefficients presupposes discrimination between the groups, that is, a gap in the outcome that is not attributable to gap in inputs (or, predictors). This does not bias the statistical exercise or taint it with the investigator's preconception of existence of bias—the results of the decomposition of the wage gap, as we shall see shortly, allows for the slope coefficients to be the same for the two groups.

One decomposition that is prominent in the discrimination literature results from the concept that there is some non-discriminatory coefficients vector that should be used to determine the contribution of the differences in the predictors. Let β^* be such a non-discriminatory coefficients vector. The outcome difference can then be written as

$$R = \left[E(X_A) - E(X_B)\right]' \beta * + [E(X_A)'(\beta_A - \beta^*) + E(X_B)'(\beta^* - \beta_B)] \tag{4}$$

This way, we have a twofold decomposition where the first component is the part of the outcome differential that is 'explained' by group differences in the predictors (the 'quantity effect') and the second summand is the 'unexplained' part. The latter is usually attributed to discrimination.[1] It may be noted here, that in case of absence of significant discrimination—which is indeed the ideal scenario—the latter part

[1] But it is important recognize that it also captures all potential effects of differences in unobserved variables.

may be approximated to be insignificant. In such a case, $\beta^*=\beta_A$ and $\beta^*=\beta_B$; thus $\beta_A=\beta_B$, i.e. slope coefficients are same for the two groups.

The determination of the components of the two-fold decomposition is made complex by the requirement of an estimate for the unknown non-discriminatory coefficient β^*. Several suggestions have been made in the literature. For example, there may be reason to assume that discrimination is directed towards one of the groups only, so that $\beta^*=\beta_A$ or $\beta^*=\beta_B$. Often, however, there is no specific reason to assume that the coefficients of one or the other group are non-discriminating. Moreover, economists have argued that the undervaluation of one group comes along with an overvaluation of the other. Faced with this dilemma, Cotton 1988 suggests weighting the coefficients by the group sizes. Others have suggested to use β^* to represent the slope coefficients obtained by pooling all observations across the two groups—the so-called pooled coefficients. This paper will proceed to use pooled coefficients.

3 Literature Review

Blinder (1973) and Oaxaca (1973) introduced the use of decomposition of outcomes to study the relative roles played by differences in inputs and differences in coefficients in influencing differences in outcomes. The methodology was further refined by Cotton (1988) and Banerjee and Knight (1983). Further, this method has been widely employed to statistically characterize group-wise gaps in wages (see for example Kim, 2010 and Bhaumik and Chakrabarty, 2009) and other outcomes (more recently in Haddad et al. 2012).

Studies on India-centric research themes include Borooah (2005), which analyses poverty and inequality in the caste discrimination framework. Using the similar technique of decomposition of economic outcomes in India over data collected for 28,922 households, it found that at least 33% of the differences in average outcome between upper caste households and SC/ST households was on account of unequal treatment—the so-called unexplained differences—of the latter. Similarly, Poel and Speybroeck (2009) decomposes malnutrition inequalities between SC/ST and the remaining Indian population using Blinder–Oaxaca decomposition of the 1998–1999 Indian Demographic Health Survey data; it reveals no significant unexplained differences between SC/ST and the remaining population, most of the differences being accounted for by differences in inputs.

Among the important papers on gender wage gap in India are the following: Reilly and Dutta (1996) discover that the average wage gap between males and females was relatively stable in 1980s and 1990s. Madheswaran and Khasnobis (2007), while focusing on decomposition of gender wage gaps, discover that gross wage gap between males and females declined over time. They also find that closing of the endowment differences contributed to the narrowing of the wage gap over time while a worsening of endowment differences in casual labour market led to the opposite trend in outcomes. Khanna (2012) goes a step forward and investigates the gender wage gap in India using NSS 66th Round data at various quintiles of the wage distribution, discovering a phenomenon of 'sticky floor' with

wage gaps being wider at left tail of the wage distribution. This paper employs the Machado–Mata–Melly decomposition which is a finer extension of the Blinder Oaxaca decomposition methodology, as outlined above. Other quantitative assessments in the Indian context include Duraisamy and Duraisamy (1996) and Kingdon and Unni (1997).

So far as the researcher's knowledge is concerned, no paper so far has analysed the gender wage gap for pooled wage market or the urban and/or rural wage market, nor has there been any comparison of such gaps in an inter-state framework. This work intends to make a contribution in this direction, by investigating the decomposition of gender wage gap in the wage market for India and comparing the results thereby obtained with the decomposition outcomes for groups of state(s).

4 Data Analysis and Findings

As mentioned earlier, this paper relies on the NSS 66th Round, which is a comprehensive data set with coverage of all relevant indicators for the current investigation. Choice of variables to be used as predictors is guided by insights offered by previous studies on the subject.

The data figuring in NSS 66th Round dataset corresponds to the relevant data items captured in NSS Questionnaire Schedule 10 used for the survey. A brief discussion of the variables used is given here, to facilitate better understanding of the analysis and its results.

Wages are recorded on a weekly basis, as 'wage and salary earnings (received or receivable) for the work done during the week'. For the econometric exercise in this paper, daily wage has been computed (with adjustment for number of days worked and the wages received thereby) and then the log form of the same has been taken. This measure is then decomposed into explained and unexplained parts using regressors such as age, levels of education (general and technical), duration of training, and number of workers in the economic enterprise.

Age is accepted as a standard measure of experience in the labour market and hence is expected to significantly influence wages. Educational level, apart from experience, is also accepted as an important determinant of wages. The utility of educational level is not only important in white-collar jobs, but throughout the labour market—this is corroborated by most studies on labour market outcomes. Duration of training contributes directly to level of skills embodied in a worker, and hence impacts wages. Number of workers in the economic enterprise is a measure of the size of the business organisation and hence likely to contribute to wage determination.

Table 1 shows a simple OLS regression carried out in order to ascertain the significance or otherwise of the variables listed above. First noteworthy fact is that controlling for all relevant regressors, gender (the variable 'sper') has a significant coefficient. This implies that the gender wage gap in wage market is existent and is statistically significant. Before moving on to analyse the characteristics of this gender wage gap, we can draw some inferences about the importance of regressors and make decisions regarding including them (or otherwise) in further econometric

Table 1 OLS regression for 'LNWAGE' in pooled wage market in INDIA

Source	SS	*df*	MS	Number of obs = 2800
Model	859.552625	29	29.6397457	$F(29, 2770) = 65.34$
Residual	1256.55959	2770	.453631621	Prob > F = 0.0000
				R-squared = 0.4062
Total	2116.11221	2799	.756024371	Adj R-squared = 0.4000
				Root MSE = .67352

lnwage	Coeff.	SE	*t*	$P > \|t\|$	[95% confidence interval]	
age	.0338685	.0013476	25.13	0.000	.031226	.0365109
sper	.2663466	.0312363	8.53	0.000	.2050978	.3275954
sector	.1432151	.0278222	5.15	0.000	.0886608	.1977695
durtrain	.0022015	.0002821	7.80	0.000	.0016484	.0027546
genedu						
5	−.0690822	.3301816	−0.21	0.834	−.7165091	.5783448
6	−.1009771	.2901621	−0.35	0.728	−.6699331	.4679788
7	.0281064	.2808516	0.10	0.920	−.5225933	.5788061
8	−.0051885	.2784318	−0.02	0.985	−.5511434	.5407664
10	.1653013	.2777561	0.60	0.552	−.3793287	.7099313
11	.3523831	.2790877	1.26	0.207	−.1948578	.899624
12	.3728184	.2771717	1.35	0.179	−.1706657	.9163024
13	.4873499	.2785958	1.75	0.080	−.0589265	1.033626
techedu						
1	.2573965	.3901685	0.66	0.509	−.5076539	1.022447
2	.634934	.3955719	1.61	0.109	−.1407116	1.41058
3	.5374178	.4237469	1.27	0.205	−.293474	1.36831
4	.0516824	.3927189	0.13	0.895	−.718369	.8217338
5	.285559	.3984372	0.72	0.474	−.495705	1.066823
6	−.1994413	.4119898	−0.48	0.628	−1.007279	.6083968
7	.0666689	.3928569	0.17	0.865	−.7036529	.8369908
8	.357009	.5159694	0.69	0.489	−.6547146	1.368733
9	.4306847	.3965097	1.09	0.277	−.3467998	1.208169
10	.4178639	.4157283	1.01	0.315	−.3973049	1.233033
11	−.2065063	.4449516	−0.46	0.643	−1.078977	.665964
12	.3510253	.3943233	0.89	0.373	−.422172	1.124223
noworker						
1	.0641983	.0765529	0.84	0.402	−.0859083	.2143049
2	.3505684	.0797635	4.40	0.000	.1941664	.5069704
3	.3749903	.0800096	4.69	0.000	.2181057	.5318749
4	.6067753	.0747439	8.12	0.000	.4602159	.7533346
9	.5122803	.0810249	6.32	0.000	.3534049	.6711557
_Cons	3.107199	.4872342	6.38	0.000	2.15182	4.062578

Table 2 B-O decomposition of wage gap in overall wage market

Blinder Oaxaca decomposition					Number of obs. = 2800	
					Model = linear	
Group 1: sper = 1					N of obs 1 = 2119	
Group 2: sper = 2					N of obs 2 = 681	
lnwage	Coeff.	Robust SE	z	$P > \|z\|$	[95% confidence interval]	
Overall						
Group_1	5.6972	.0179605	317.21	0.000	5.661999	5.732402
Group_2	5.364171	.0363132	147.72	0.000	5.292999	5.435344
Difference	.333029	.0405121	8.22	0.000	.2536268	.4124312
Explained	.103883	.0209089	4.97	0.000	.0629024	.1448636
Unexplained	.229146	.0336466	6.81	0.000	.1632	.2950921

exercises. Apart from gender, duration of vocational training in weeks (the variable 'durtrain'), age of the individual in the wage labour market (the variable 'age') and the number of workers in the enterprise (the variable 'noworker') are found to be significant determinants of wages—therefore it is imperative that we include them in further econometric expositions. However, coefficients for levels of technical education (the variable 'techedu') and general education (the variable 'genedu') are all insignificant, hence we decide to drop these variables from our econometric exercises hereinafter.

We now proceed to dissect the wage gap between males and females into explained and unexplained parts, using pooled coefficients as the benchmark (as explained in the Methodology section); further we will compare and contrast our results with comparable findings in rural and urban wage markets for a holistic understanding. Table 2 shows the Blinder–Oaxaca decomposition for the gender wage gap in the pooled wage market. At the aggregate level, average of log of wages for males (sper = 1) is 5.6972 while that for females (sper = 2) is 5.364171; the difference between these values comes to 0.333029, which is statistically significant at 5% level of significance. It clearly shows that the gap in log wage between males and females is statistically significant and the unexplained portion of the gap is more than twice the explained portion of the gap, i.e. while the explained gap is one-third of total gap in log of wages (0.103 out of 0.333), the unexplained gap (0.229 out of 0.333) is two-thirds of total gap. Therefore, although the statistically significant gap in log of wages between males and females at the aggregate wage market is partly explained by difference in observable characteristics that are accounted for, the major component of the gap is unexplained—which points to discrimination between males and females in the Indian wage market. At the holistic level of analysis, it is easy to grasp that the unexplained gap can only be attributed to discrimination (in terms of differences in rates of return to characteristics that fetch a premium in the wage market) and not to unobservable characteristics that cannot be quantified in analysis.

Table 3 B-O decomposition of wage gap in rural market

Blinder Oaxaca decomposition					Number of obs. = 958	
					Model = linear	
Group 1: sper = 1					N of obs 1 = 743	
Group 2: sper = 2					N of obs 2 = 215	
lnwage	Coeff.	Robust SE	z	$P > \|z\|$	[95% confidence interval]	
Overall						
Group_1	5.482501	.0294406	186.22	0.000	5.424798	5.540203
Group_2	5.147828	.0622998	82.63	0.000	5.025723	5.269933
Difference	.3346726	.0689059	4.86	0.000	.1996196	.4697256
Explained	.0959028	.0334404	2.87	0.004	.0303608	.1614448
Unexplained	.2387698	.0584964	4.08	0.000	.124119	.3534206

Table 4 B-O decomposition of wage gap in urban market

Blinder Oaxaca decomposition					Number of obs. = 1842	
					Model = linear	
Group 1: sper = 1					N of obs 1 = 1376	
Group 2: sper = 2					N of obs 2 = 466	
lnwage	Coeff.	Robust SE	z	$P > \|z\|$	[95% confidence interval]	
Overall						
Group_1	5.813132	.022016	264.04	0.000	5.769982	5.856283
Group_2	5.463987	.0438641	124.57	0.000	5.378014	5.549959
Difference	.3491456	.0490791	7.11	0.000	.2529523	.445339
Explained	.1114921	.0257131	4.34	0.000	.0610953	.161889
Unexplained	.2376535	.0407123	5.84	0.000	.1578588	.3174482

For purposes of comparison, we study using the same econometric specification the gender wage gap in rural wage market. Table 3 shows the results, which are broadly in line with those obtained for the pooled wage market. The gap in log wage between males (average log of wages = 5.482) and females (average log of wages = 5.147) is statistically significant at the chosen level of significance and the unexplained portion of the gap (0.238 of 0.334) exceeds the explained portion of the gap (0.095 of 0.334) by a factor of 2.5, i.e. while the explained gap is 29% of the total gap in log of wages, the unexplained gap is 71% of total. Although the gap in log of wages between males and females roughly remains comparable at the aggregate and the rural level, the role played by discrimination in comprising the gap is much higher in the rural wage market vis-à-vis the aggregate wage market—with correspondingly smaller role played by difference in observable characteristics. Further, we dissect the gender wage gap for urban wage markets—using the same econometric specification as before. Table 4 exhibits the results: the gap in log wage

Table 5 B-O decomposition of wage gap in wage market of rich states

Blinder Oaxaca decomposition					Number of obs. = 927	
					Model = linear	
Group 1: sper = 1					N of obs 1 = 704	
Group 2: sper = 2					N of obs 2 = 223	
lnwage	Coeff.	Robust SE	*z*	*P* > |*z*|	[95% confidence interval]	
Overall						
Group_1	5.637687	.0319755	176.31	176.31	5.575016	5.700358
Group_2	5.303739	.0667315	79.48	79.48	5.172947	5.43453
Difference	.3339482	.0739968	4.51	4.51	.1889171	.4789792
Explained	.145861	.0391978	3.72	3.72	.0690347	.2226873
Unexplained	.1880872	.0614563	3.06	3.06	.067635	.3085393

between males and females (i.e. 0.3491) is statistically significant and the unexplained portion of the gap (0.111) exceeds the explained portion of the gap (0.237) by a factor of 2, i.e. while the explained gap is one-third of the total gap in log of wages, the unexplained gap is around two-thirds of the total. Similar to the observations for the aggregate wage market (in Table 2), the statistically significant gap in log of wages between males and females at the aggregate wage market is partly explained by difference in observable characteristics that are accounted for but the major component of the gap is unexplained. The extent of the log wage gap attributable to discrimination (i.e. 67%), however, is less in comparison with rural wage market (where it is 71%).

Further comparison with states at the diametrically opposite end of the income scale yields interesting insights. Analysing gender wage gap in the rural wage market of high per capita income states like Haryana, Maharashtra, Tamil Nadu and Gujarat (Refer to Notes for selection of states)—results shown in Table 5—we see that albeit the gender gap is statistically significant, the unexplained gap is slightly more than the explained gap, i.e. the explained and unexplained gaps are approximately 45% and 55%, respectively, of the total gender gap in wages. Clearly, discrimination in terms of difference in rates of return to market-valued labour characteristics is much less in high per capita income states. By contradistinction, for states at the lower end of per capita GDP scale like Bihar, Uttar Pradesh, Jharkhand, Madhya Pradesh and Odisha—the results for which are given in Table 6—the gender wage gap is statistically significant and explained and unexplained portions of the gap are more or less equal. Thus, the foregoing analysis seems to suggest that gender discrimination in the wage market gets magnified with per capita incomes, at this reference point of analysis.

Some caveats, however, ought to be kept in mind while interpreting the aforementioned results:

1. The numbers of observations available for state-wide analyses, albeit qualifying for the large sample treatment, may be judged by some scholars as not being

Table 6 B-O decomposition of wage gap in wage market of poorer states

Blinder Oaxaca decomposition					Number of obs. = 281	
					Model = linear	
Group 1: sper = 1					N of obs 1 = 236	
Group 2: sper = 2					N of obs 2 = 45	
lnwage	Coeff.	Robust SE	z	$P > \|z\|$	[95% confidence interval]	
Overall						
Group_1	5.775081	.0605871	95.82	0.000	5.656333	5.89383
Group_2	5.3047	.1557676	34.06	0.000	4.999401	5.609999
Difference	.4703812	.1671357	2.81	0.005	.1428012	.7979611
Explained	.2205466	.0964197	2.29	0.022	.0315676	.4095257
Unexplained	.2498345	.1226173	2.04	0.042	.009509	.49016

large enough to draw wage gap comparisons. While appreciating this view point, it may be pointed out that NSS Data is inarguably the most comprehensive data available for undertaking analyses of the above nature and hence in absence of a better alternative, the given dataset must be treated as acceptable.

2. The unexplained part of the wage gaps, as mentioned elsewhere, also captures all potential effects of differences in unobserved variables. Therefore, labelling all of the unexplained fractions of the wage gaps as discrimination is technically unsound. However, the very fact that a significant gap in wages along the axis of gender is not explained in terms of differences in characteristics/inputs raises doubts about the gender-based equality of value of labour.
3. Even as we 'explain' parts of the gender wage gap in terms of differences in characteristics or inputs, such decomposition exercises fail to capture discrimination faced in access to or acquisition of such characteristics or inputs. This is often called 'premarket discrimination' (see for example Juhn et al. 1993)—that is, the discrimination that members of a group(s) experience while trying to acquire the characteristics or credentials that receive a premium in the wage market. In our instant case, discrimination faced by women (or men) faced in accessing levels of general education, levels of technical education, vocational training, gaining employment in enterprises employing varying levels of workers, etc., is not captured by our Blinder–Oaxaca decomposition. This is as much a strength as a demerit. While the full spectrum of discrimination fails to get captured, this exercise illustrates that 'equality in access to inputs' does not lead inexorably to 'equality in outcomes' for groups. The policy implication of this is that efforts to mitigate discrimination in the labour/wage market must be pursued as vigorously as efforts to end the discrimination in the access to valuable inputs such as education, health, skilling.

5 Conclusion

The basic conclusion one may draw from the foregoing analysis is that viewed at an aggregate level, the gender gap in wages is not just significant, but two-thirds of it cannot be explained on the basis of observable and relevant labour market characteristics; and by implication, two-third of this gap is attributed to discrimination in the pooled wage market against females vis-à-vis males. Juxtaposing this with the results for urban wage market of India and rural wage market of India shows that results are largely similar. Furthermore it is seen that data suggests that gender gap in wages in high per capita GDP states such as Haryana, Maharashtra, Gujarat and Tamil Nadu as well as in low per capita GDP states like Odisha, Jharkhand, Bihar, Uttar Pradesh and Madhya Pradesh is significant. The difference is that whereas the explained and unexplained gap for the latter category of states is more or less the same, for the former category unexplained gap (which signifies discrimination) is relatively greater. Albeit recent data or more detailed studies with wider coverage than NSS Rounds may also afford opportunities to revisit the findings of this research, evidence is overwhelming that there is need for concrete steps to eliminate the discrimination observed against females in the wage market if we want to become a 'Smart Economy' in coming days. The ascending levels of women's participation in the paid labour market activities is considered as a phenomenon with salutary impact on improving women's status by bridging the chasm in this crucial sphere of economic involvement. However, simplistic hikes in participation remain inadequate in altering the gender inequalities unless these are accompanied by women undertaking work that is decent, lucrative, equally remunerative and secure. If unlettered females are crowding into unskilled, manual labour-requiring jobs, that are low paying and hazardous to their health and safety, such a situation can hardly be healthy or praiseworthy. Equally despicable is co-qualified and co-capable women earning less than their comparable male counterparts. Therefore, in addition to the policy focus and implementation of programs those aim at magnifying female labour force participation, nuanced safeguards and supporting institutions must also be put in place to ensure the principle of gender equality in wage markets in India.

6 Notes

1. The codes used for levels of general education (represented in the tables as 'genedu') in the NSS Questionnaire Schedule 10: Employment and Unemployment are—not literate—01, literate without formal schooling: EGS/ NFEC/ AEC—02, TLC—03, others—04; literate: below primary—05, primary—06, middle—07, secondary—08, higher secondary—10, diploma/certificate course—11, graduate—12, postgraduate and above—13.
2. The codes used for levels of technical education (represented in the tables as 'techedu') in the NSS Questionnaire Schedule 10: Employment and Unemployment are—no technical education—01, technical degree in agriculture/ engineering/ technology/ medicine, etc.,—02.

3. Diploma or certificate (below graduate level) in: agriculture—03, engineering/ technology—04, medicine—05, crafts—06, other subjects—07; diploma or certificate (graduate and above level) in: agriculture—08, engineering/ technology—09, medicine—10, crafts—11, other subjects—12.
4. The codes used for number of workers in the enterprise (represented in the tables as 'noworker') in the NSS Questionnaire Schedule 10: Employment and Unemployment are—less than 6—1, 6 & above but less than 10—2, 10 and above but less than 20—3, 20 & above—4, not known—9.
5. The codes used for sex of the individual (represented in the tables as 'sper') in the NSS Questionnaire Schedule 10: Male—1, Female—2.

References

Banerjee, B., and J.B. Knight. 1983. Caste discrimination in the Indian labour market. *Journal of Development Economics* 17(1985): 277–307.

Bhaumik, S.K., and M. Chakrabarty. 2009. Is education the panacea for economic deprivation of Muslims: Evidence from wage earners in India, 1987–2005. *Journal of Asian Economics* 20(2): 137–149.

Blinder, A.S. 1973. Wage discrimination: Reduced form and structural estimates. *The Journal of Human Resources* 8: 436–455.

Borooah, V.K. 2005. Caste, inequality and poverty in India. *Review of Development Economics* 9(3): 399–414.

Cotton, J. 1988. On the decomposition of wage differentials. *The Review of Economics and Statistics* 70: 236–243.

Duraisamy, M., and P. Duraisamy. 1996. Women in the professional and technical labour market in India: Gender discrimination in education and employment and earnings. *Indian Journal of Labour Economics* 42(4): 599–612.

Haddad, S., K.S. Mohindra, K. Siekmans, G. Mak, and D. Narayana. 2012. Health divide between indigenous and non-indigenous populations in Kerala. *BMC Public Health* 12: 390.

ILO. 2016. *Women at work: Trends 2016*. International Labour Organisation.

ILO website www.ilo.org.

Jann, B. 2008. The Blinder Oaxaca decomposition for linear regression models. *The Stata Journal* 8(4): 453–479.

Khanna, S. 2012. *Gender wage discrimination in India: Glass ceiling or sticky floor?* CDE working paper no. 214. https://ssrn.com/abstract=2115074.

Kim, C.H. 2010. Decomposing the change in wage gap between white and black men over time 1990–2005. *Sociological Methods and Research* 38(4): 619–651.

Kingdon, G.G., and J. Unni. 1997. Education and women's labour market outcomes in India. *Education Economics* 9(2): 173–195.

Madheswaran, S., and Khasnobis, B. G. 2007. *Gender discrimination in the labour market: Evidence from the NSS*. WIDER research project on gender wage gap and its impact on poverty: evidence from India.

Oaxaca, R. 1973. Male–female wage differentials in urban labor markets. *International Economic Review* 14: 693–709.

Poel, E.V., and Niko Speybroeck. 2009. Decomposing malnutrition inequalities between SC/STs and the remaining Indian population. *Ethnicity and Health* 14(3): 271–287.

Reilly, B., and Dutta, P. V. 1996. *The gender pay gap and trade liberalisation: Evidence for India*. Poverty research unit at sussex working paper no. 3.

WEF. 2016. *The global gender gap report 2016*. Accessed online.