Gender Discrimination and the Biased Indian Labour Market: Evidence from the National Sample Survey

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Abstract

Gender gaps in wages are a reflection of inequality and discrimination. This exists across region, sector, type of work and other divisions. Discrimination, is a presence of inequalities between male and female workers with similar skills and in similar occupations. Therefore only understanding wage inequality may be looking at the problem partially. Using the Indian National Sample Survey 2011-12, this paper examines the facets of gender-based wage inequality and discrimination in regular and casual workers. First, Theil index is calculated to interpret within and between groups inequalities. Then, a Three-fold Oaxaca decomposition method is utilised to divide the wage gaps between explained, unexplained and interaction components. We show that even though the returns on education are higher for women than men at each level of education, females continue to earn less. Results clearly indicate a high raw wage differential of 51.5 percent, which is divided into three portions of which the endowment is significantly low at 3.1 percent percent and a much higher indispensable discrimination (coefficient) is 37.9. Discrimination is greater in regular employment as compared to casual employment; higher in urban as compared to rural region. We show that women workers are discriminated against on the basis of age. Policies need to emphasise on not just improving female participation but also to maintain it. The need is for sincere efforts in improving access to the labour market through training programs specially designed for women that incorporate dealing with complexities such as child care, maternity benefits, transportation and even safety. Putting awareness at the core of a long-grained thought process that discourages distribution of unpaid or care work and sees it primarily as a ‘women’s job’ may create a less discriminating and unbiased labour market for Indian women.

Keywords: gender inequality, Theil index, Threefold Oaxaca decomposition, wage discrimination. NSS (EUS) 68th round, NCO 2004, returns to education.

JEL Classification: I26, J01, J16, J31, J70.

Highlights

1. Theil index inequality is higher in urban areas and 'within group' inequality is higher for all divisions.
2. Regular sector shows higher inequality as compared to the casual sector, contrary to the perception of higher wage inequalities and discrimination in casual employment.
3. Despite the presence of advantage to female workers in certain occupations, the absolute advantage is not very significant.
4. Endowment component is 3.59 percent, discrimination explains 94 percent and interaction 2.42 percent of total wage gaps.
5. Miniscule earning advantage for female workers in NCO 2 and 3 with adjusted wage differential of 0.12 and 0.01 respectively.

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1. Introduction

Gender inequalities and discrimination prevail in distinct forms across sectors and divisions all over the world. Such discriminations prevent women from opportunities that are needed to create an equal, just and prosperous society (UN in India, 2020; SDG 5: Gender Equality). Although women in India constitute about half the total population, their contributions to the economy in terms of paid labour are far lower than that of men. With women typically spending more time in unpaid care work as compared to men in addition to their paid activities, if any, creates a “double burden” of work. In comparison to men, women are spending more time ‘on an average two to ten times' on care activities (Ferrant et al., 2014). Such unequal distribution of unpaid care work can explain unequal opportunities to participate at par in paid work. We do see a well documented negative correlation between the female labour force participation rate and unpaid care work (Miranda, 2011; Ferrant et al., 2014) where care itself can have implications either increasing ‘capabilities and choices’ for women or restricting them to ‘traditional roles’ such as ‘motherhood’ (Razavi, 2007). To make things worrisome, care work is also linked with higher chances of “occupational downgrading”, where women may accept part-time, sub-standard work or vulnerable employment (Hegewisch & Gornick, 2011). Indian women on an average spend upto 577 percent more time than men on domestic work; compared internationally they spend at least 40 percent more time than South African or Chinese women (OECD, 2021).

So we do fare poorly in terms of the female Labour Force Participation Rate (see Endnotes 1) in comparison to that of other developing and middle-income nations. This rate declined to 23.3 percent in 2017-18 which means that three of four women were neither employed nor looking for employment. A significant decline in the rural areas is witnessed where the female Labour Force Participation Rate (LFPR) declined by 7 percent, despite the male participation rate remaining roughly the same. As documented in the National Sample Survey (NSS) rounds and Participatory Labour Force Survey (PLFS) for the period of 1999-00 to 2017-18, it is observed that male worker participation has remained more or less in both rural and urban areas (from 53.1 percent for rural and 51.3 percent in urban region in 1999-00 to 51.7 percent in rural and 53 per cent in urban region in 2017-18); the female participation has dwindled from 25.9 percent in 1999-00 to a mere 16.5 percent in 2017-18 (where the drop in rural participation is more significant at 42.4 percent).

Female rate of labour participation is not only an important indicator of their own individual development and empowerment but also their role in economic development, and these two are interdependent. Our labour market remains burdened with vast inequalities, on the lines of gender identity differences are manifested through unequal access of opportunities to those with equal capacities to work and manifested through unequal pay for equal tasks (Lama & Majumder, 2018). Majority of India's female workers figure either in abysmally poor remunerating jobs of the unorganised informal sector, where they are neither entitled to maternity leaves and overtime pay, nor to a safe and dignified working environment, or in unpaid jobs as primary care-givers in the family (ILO 2013). Even though in recent years India has narrowed the gender gap, which is now at 68 percent across sectors such as education, political representation and health, of which a significant accomplishment is in primary and secondary school enrolments (GOI & Ministry of Human Resource & Development, 2018).

Studies have analysed the falling female participation and attributed this decline to different factors: Of course our cultural and social behaviours "dissuade women's participation in the labour market" (Srivastava & Srivastava, 2010). Decline could be attributed to lack of employment opportunities specially for rural women in the non-farm sector (Ramesh & Srivastava, 2014; Kannan & Raveendra, 2012). Another, is a rise in household income and increase in the number of school enrolments (Bhalla & Kaur, 2011). Interestingly more girls being at school can be a possible reason for mothers to withdraw from employment to care for younger children at home (Krishna et al., 2016). Yet another, mechanisation of agriculture is seen as a cause for lowering female participation in the rural areas (Verick, 2018).

Whatever the causes, whether this decline is due to supply side constraints or contraction in demand, has colossal reverberations on the understanding of the country's economy and its policy formation initiatives. If it is a matter of 'personal choice' to drop out of the workforce due to 'rising' family incomes (Madheswaran & Shroff, 2000), then it is not an issue requiring policy interventions and its impact on the economy might not be as deleterious. But, if more women are staying out of the labour market either because of lack of jobs in the market or unfavourable working circumstances, then we seriously need to review our policies and take relevant measures to encourage women to join the workforce in order to make up for the economic losses resulting thereof.

Gender gaps in wages is a reflection of 'gross inequality and discrimination' (Esteve & Berta, 2004), that exists across location (rural and urban), sector (public and private), type of work (regular and casual), occupations, industry and other divisions (Das, 2012), the later (discrimination) though is a presence of inequalities between male and female worker for the same job with same level of skill (Mehrotra, 2020). Since simply understanding wage inequality may be looking at the problem partially, we attempt to examine the facets of not only inequality but also understand and measure the extent of discrimination against women in the regular and casual employment in the Indian Labour market (Thomas, 2012). In the subsequent sections, we present an overview of literature in Section 2. Section 4 provides an overview of the data sources and methodology. Explanation of the Theil index and it's decomposition, the Blinder Oaxaca Decomposition methods is provided in Section 4. We calculate the Returns to Education and its explanation in Section 5. Section 6 discusses results of the Theil index and its decomposition, the Earnings function results along with the average rate of returns to education to male and female workers, and the Blinder Oaxaca decomposition. Section 7 concludes with Discussion.

2. Literature

Prevalence of unequal wages with unequal types of employment, regional differences or different sectors depicts wage disparities, however, we also see unequal wage between men and women who have similar levels of skill and education and are in the same jobs (Lama & Majumder, 2018; Majumder, 2011; Rustagi, 2005 and Agarwal, 1993). This is discrimination and genger bias, which is largely prevalent. Deshpande et al., 2015 have analysed gender discrimination for salaried workers using the NSSO data for 1999-00 and 2009-10. Using the Blinder- Oaxaca and the Machado-Mata-Melly decompositions they show large unexplained wage gaps over the decade. Interestingly, such gaps are found to be greater at the "lower ends of wage distribution" which is also documented as prevalence of "sticky floor" in literature.

Wage imbalances across men and women remain despite increase in overall wages (Dev, 2002; Rustagi, 2005) and variations in the female labour participation influencing the remuneration and returns due to them. Early studies such as by Becker (1957), Banerjee (1999) and Deshpande &

Deshpande (1999) and Dev (2002) have analysed differences in wages of men and women, especially those which have same level of educational attainments and doing similar work, thus showing “discrimination against women due to noneconomic considerations” (Craig et al., 1985). Zajkowska (2013) using Oaxaca decomposition method shows significant disparities between monthly wage of male and female workers, and even a higher rate of return to schooling and jobs for men in the Polish labour market. A similar discrimination in the Indian labour market is seen using oaxaca decomposition methods, where more than endowments, there seems to be prevalence of discrimination (Agarwal, 2013). A high level of discrimination against women is also documented by Kingdon & Unni (2001) regardless of the educational attainment. The contribution of education as a discriminatory factor is studied by Kingdon (1998) showing bias by parents against the girl child regardless of the financial condition of the family. In a broader sub-groups divided on the basis of caste, region and language along with gender, Kumar & Iqbal (2020) show disparities prevalent in both rural and urban areas. They show caste-based disparities in educational attainment and differences in educational attainment between male and females within the same caste; showing a clear and significant stratification despite implementation of reservation policies in the country.

Even though the impact of education on job opportunities and wages is not a new idea (Randall et al., 1980; Dolton & Kidd, 1994), the relationship between supply of female labour force and education level among Indian females is not extensively documented. Nevertheless, few attempts have focused on ‘intrinsic’ advantages of education, and analysing investment decisions on education among females in India. Sidkar (2019) is a recent extensive attempt to determine wage differentials in ‘formal’ and ‘informal’ sectors classified on the basis of gender, showing an insignificant relationship between wages and education levels, and yet persons with higher educational level are able to get better jobs, and interestingly this remains largely true for those who are part of the socially deprived sections, but not for females, thus showing a higher gender discrimination as compared to social discrimination in the Indian labour market.

Additionally, understanding female labour supply is complicated and multidimensional depending on a person's job orientation, effort and remuneration related factors (Rustagi, 2005 and Majumder, 2011). Several non-wage factors such as unequal work conditions, lack of social security benefits and even additional responsibility of the household and domestic chores remain to be seen as influencing supply of women in the labourforce. This makes a women's labour supply behaviour distinct from that observed for male labour in terms of age of entry, inherent human capital attributes, marital status and social class position affecting their mobility in public spaces, fertility or reproduction and so on (Rustagi, 2005). Interestingly enough, it is established that a part of the delay in age at entry into the labour market also relates to the educational pursuits among women as well as men (van Hek et al., 2016). At higher educational levels, women are outperforming men and yet the gender disparity in the educational status of the labourforce is more skewed as compared to the overall population due to the association with income status (Agarwal, 2006).

Agarwal, 2013 has examined gaps using the NSS survey between male and female workers separately for rural and urban regions using oaxaca decomposition finding significant wage differences that are largely attributed to discrimination. Similarly, Poddar & Mukhopadhyay (2018) using the NSSO data from the 68th round explain the presence of 'chronic direct discrimination against women'. However, they also argue insensitivity in the labour market, largely dominated by male workers and even a portion of wage gap attributed to lower skill and experience among female workers. More recently, Balakarushna et al. (2019) have studied wage gaps between male and female workers in India's urban labour market following the Blinder-Oaxaca decomposition. Such studies have found considerable disparity in employment and earning standards showing female workers at a disadvantage position as compared to male workers, they also suggest that such differences are largely attributed to discrimination than to endowment and is visible across sectors, region and religion.

3. Data Sources, Number of Observations, Use of Variables and Methodology

Micro-individual data file for the NSSO 68th round (2011-12) is accessed to calculate both the Theil index and its decomposition, and the Oaxaca decomposition. We focus on wages paid in cash and kind and are calculated for daily payment. We convert wages given as current weekly status (CWS) in the NSS data files to average daily rate. For this we divide the total wage received during the given week by the total number of days in each activity. Daily wage is thus derived as a ratio of given weekly wage and number of full day work in the reference week. To estimate the earnings differences attributed to discrimination, we use Mincerian earnings function for sub-groups based on gender. For notification purposes, we use 'f' for female workers, and 'm' for male workers. We take the value of the dependent variable of probit (selection) as 1 if an individual wage is > 0, and 0 otherwise. The natural logarithm of the daily wage rate is used as the dependent variable, while age, levels of education, region, sector, occupation and industry are used as predictors. For occupational classification, Broad occupational divisions given under NCO 2004 are utilised.

This paper includes persons belonging to rural and urban areas and regular and casual workers. We exclude self employed workers. Workers are considered individuals between 15 to 59 years of age with non-zero income. Social and religion-based segregation is excluded from this analysis.

Two approaches are used in this paper to analyse discrimation in wage and employment. First, disparities at aggregate levels are examined by using the Theil index in wage distribution. We do this by gender, sector, region and activity status of the workers. Although the Gini Coefficient and the Theil index of inequality (which was originally proposed by Theil, 1967) are two most frequently used inequality measures (Charles-Coll & Jorge, 2011), Theil index is preferred (Allison, 1978), recognised in standard reference works on income distribution (Cowell, 2003) and widely applied in social sciences more so due to its decomposability (Liao, 2016). Subsequently decomposing the Theil index. This method allows us to determine the extent of gender discrimination attributable to 'within groups' or 'between groups' componetnt. We use STATA software where Stephen P. Jenkins model of Theil index (Jenkins, 1999) has an inbuilt 'ineqdeco' command.

Our second method involves the Oaxaca decomposition technique (see Endnotes 4) that seperates the observed wage gap into 'endowment' and 'coefficient' components. Here, the total gap between the average wage of male and female workers are separated or decomposed into 'explainable factors' those that could be due to occupational segregation; and 'unexplainable factors' those that are direct gender discrimination (Blinder 1973; Oaxaca 1973). We use the STATA inbuilt command "oaxaca" developed by Ben Jann (Jann, 2008). Subsequently we use the simple OLS regression based on Mincer (1974) that is widely used in economic studies to estimate returns on schooling along with 'impact of work experience on gender wage differences' (Heckman et al., 2003) to analyse the impact of factors such as education and occupation on wages.

Returns to Education is as an important calculation to find out the extent of inequality faced by females at each level of educational attainment and whether they do face any barriers in climbing the educational ladder. The NSS E&U survey data gives the 'completed level of education' for every individual as the level of 'general education' which means the maximum level of education completed. Codes (Endnotes 5) assigned for all levels of education are as follows: Primary - 06, middle - 07, secondary - 08, higher secondary - 10, diploma/ certificate course - 11, graduate - 12 and postgraduate and above - 13.

We use different dummy variables for controlling characteristics such as gender, type of employment (regular or casual), area (rural or urban), using the Mincerian wage equation. To give a better representation to the main determinants of wage along with individual characteristics, education and area, we also include job characteristics and occupational division of workers. For classification of occupations: dummy variable groups are formed for 9 divisions of occupational classification as given under the NCO 2004. For the purpose of classifying these occupations based on the intensity of task and skill component, we bring together these 9 classifications as three broad classifications; grouping them into high skilled, middle skilled and low skilled occupations (see Notes 2). We have shown descriptive statistics and dummy variables in Appendix Table 1.

Notwithstanding the fact that one does acquire better work life and standards with higher education level, considering wage as an important element, we relate wage with educational level, separately for female and male workers. There are few studies in the past that have attempted returns to education in India by gender and sector, limited studies calculate returns to education over time.

4.1. Explanation of the Theil Index and Decomposition

The total inequality measured by Theil's T is written as:

$$T = \frac{1}{N}\sum_{i=1}^{N}\frac{x_i}{\bar{x}}\ln\frac{x_i}{\bar{x}} \tag{1}$$

where xi = income of the individual i, x = mean income and N = sample size.

Using the same notation, equation (1) can be decomposed as follows:

$$T_b = \sum_{k=1}^{K} y_k \ln\frac{\bar{x}_k}{\bar{x}} \tag{2}$$

where yk = kth group's income share as a proportion of the sample or total income of the population group, xk = mean income of sub-group k therefore, within component can be written as:

$$T_w = \sum_{k=1}^{K} y_k \sum_{i=1}^{n_k} y_{ik} \ln\frac{x_{ik}}{\bar{x}_k} \tag{3}$$

where ik = income share of ith individual within the subgroup k and xik = ith individual's income within the k sub-group.

4.2. Explanation of the Blinder Oaxaca Decomposition Method

The gross wage differential (G) between male (m) and female (f) groups can be written as:

$$G = \frac{Y_m - Y_f}{Y_f} = \frac{Y_m}{Y_f} - 1 \tag{4}$$

where Y_m and Y_f = wages of male individuals and wages of female individuals respectively. In absence of labour market discrimination, the difference between male and female wages would reflect productivity (or difference in wages due to skill). This can be written as:

$$Q = \frac{Y_m^0}{Y_f^0} - 1 \tag{5}$$

Whereas superscript shown as 0 denotes absence of bias or market discrimination. The proportionate difference between G+1 from equation (4) and Q+1 from equation (5) gives us the market discrimination coffecient (D).

$$D = \frac{\left(Y_m / Y_f \right) - \left(Y_m^0 / Y_f^0 \right)}{\left(Y_m^0 / Y_f^0 \right)} = \frac{\left(Y_m / Y_f \right)}{\left(Y_m^0 / Y_f^0 \right)} - 1 \tag{6}$$

Substituting (5) and (6) in (4) and converting to a logarithmic expression, we get the gross earnings differential:

$$\ln(G + 1) = \ln(D + 1) + \ln(Q + 1) \tag{7}$$

To estimate the gaps in wages due to discrimination, we use the Mincrian earnings functions (Mincer, 1974) separately for male workers and female workers, the decomposition is applied within the framework of Ordinary Least Squares (OLS) Here, the male wage equation can be written as:

$$\ln \overline{Y}_m = \sum \widehat{\beta}_m \overline{X}_m + \varepsilon_m \tag{8}$$

And the female wage equation can be written as:

$$\ln \overline{Y}_f = \sum \widehat{\beta}_f \overline{X}_f + \varepsilon_f \tag{9}$$

where $\ln \overline{Y}$ = geometric means of the earnings, $\overline{X}$ = vector of mean value of regressors, $\widehat{\beta}$ = vector of coefficients and ε = error term. Substituting the values of D and Q in equation (7) and combining equations (4), (5) and (6), the gross differential can be written as:

$$\ln(G + 1) = \ln \overline{Y}_m - \ln \overline{Y}_f = \sum \widehat{\beta}_m \overline{X}_m - \sum \widehat{\beta}_f \overline{X}_f \tag{10}$$

The difference in coefficients can be considered as discrimination. In absence of discrimination if for a given endowment males and females are equally paid, then a hypothetical female earnings function can be written as:

$$\ln \overline{Y}_f = \sum \widehat{\beta}_m \overline{X}_f \tag{11}$$

Subtracting equation (11) from equation (10) we get:

$$\ln \overline{Y}_m - \ln \overline{Y}_f = \sum \widehat{\beta}_m \left(\overline{X}_m - \overline{X}_f \right) + \sum \overline{X}_f \left(\widehat{\beta}_m - \widehat{\beta}_f \right) \tag{12}$$

alternatively the decomposition equation can be written as:

$$\ln \overline{Y}_m - \ln \overline{Y}_f = \sum \widehat{\beta}_f \left(\overline{X}_m - \overline{X}_f \right) + \sum \overline{X}_m \left(\widehat{\beta}_m - \widehat{\beta}_f \right) \tag{13}$$

5.2. Estimating the Return to Schooling

The Mincerian wage equation is most commonly used in empirical literature to understand wage as a ‘function of schooling and labour market experience’, by estimating average gains with every additional year of education (Patrinos, 2016). Being a flexible model, other than showing the relationship between wages and education, it has allowed us to use other variables such as age (following conventional literature, we use age as a proxy for experience), region (rural and urban), gender, sector of employment (public and private) and occupational categories. We added categorical dummy variables to the Mincer wage earnings equation to give us wage differences across each category. Years of schooling is estimated by 'levels of schooling' or 'level of education' such as primary or secondary.

The average rate of return to each level of education is:

$$\gamma_e = \frac{\beta_e - \beta_{e-1}}{S_e - S_{e-1}} \tag{14}$$

Where, e = level of education at each level. β_e = corresponding coefficient in the wage regression and S_e = years of schooling at each educational level e. If, suppose the rate of return for primary education will be calculated, it can be denoted as follows:

$$\gamma_{Primary} = \frac{\beta_{Primary}}{S_{Primary}} \tag{15}$$

6.1. Empirical Results: Wage disparities using the Theil index

In Table 1, we mention the 90:10, 90:50 and 10:50 quantile ratios in their 2 x natural logarithmic form and we use the middle ratio as referent, that illustrate the gender gap in the income distribution. The results show that inequalities are greater in urban sectors and for regular wage earners. We do not see a high gender inequality in the casual sector workers because of the prevalence of substantially low wages of casual workers in comparison to regular salaried earners. The lower wage earned by such casual workers (both females and males) is largely due to cost cutting rather than unequal labour efficiency. As compared, therefore the gender gaps between the highest paid regular worker and the lowest paid regular worker are more pervasive in comparison to the wage gaps between highest to lowest in the casual sector.

Table 1 here

Decomposing the Theil index into 'within-group' and 'between-group' is observed in Table 2. Our figures are generally consistent with priori expectations. First stark observation is the percentage employment shares of female and male workers. Notice how across sectors, groups and employment types, male workers make up for more than two-third of the total employment share. This disparity is higher in urban areas; higher for the private sectors and higher for regular workers as compared to their respective sub-groups. Notwithstanding, casual sector gaining traction as a main source of employment to an increasing labour market, we see that even among the 23 percent workers who are salaried or regular wage workers, 71 percent have no written job contract and 54 percent are not eligible for paid leave, half of them do not have any social security benefits (PLFS 2017-18).

Next we observe the inequalities in wages as determined by the Theil index, and we notice that gender inequalities are higher in urban areas in comparison to rural areas. Infact gender wage gaps are more apparent in the private sector against the public sector, but the difference between these two is not very large in itself. The provision of reservations for women and a more organised nature of such a sector could reflect a lower inequality for the public sector. Not only the share of male workers constituted for more than two thirds of the total working population, their mean wages are significantly higher than females across sectors, irrespective of the sector or type of work. However, it is observed that regular and casual female workers upto primary level of education are better off in comparison to their male counterparts.

Rural sector absorbs a higher percentage of women workers as compared to the urban sector, along with a lower between group inequality for both sectors with a slightly higher between group inequality observed for the rural sector; 5.35 per cent of total inequality. Another interesting thing we observe is that 'within group' inequality is more than 'between group' for all divisions. For rural regions, between group inequality accounts for 5.35 per cent of total inequality, for urban workers the between group gender inequality is almost negligible, almost all inequality is attributed to within groups.

Table 2 here

6.2. Empirical Results: Earnings Function OLS

Table 3 provides earnings function results for the year 2011-12, providing insight on the connection between average years of schooling and wages among workers segregated by two gender groups. There seems to be a significant relationship for all divisions and at all educational levels, however, interestingly the impact of higher levels of education is significant for female workers as compared to male workers. This result is consistent with that from literature which has been showing a higher return to schooling for primary education, however a reversing trend showing increase in returns for tertiary education is seen (Montenegro & Patrinos, 2014; Patrinos, 2016). Even when we compare between the two groups, females show a higher level of return on education across the educational levels as compared to the males depicting the importance of increasing incentives and promoting female employment opportunities in the skewed labour market. However, it is important to remember that the female workers document a lower base level as compared to the male worker.

The mean log wages are 5.203 for males and 4.688 for females. The gender wage gap between female and male workers is - 0.715 implying a significantly lower level of female wage. As expected, all the characteristic variables are significant factors of wage for male and female, the gender gap portrays that this gap varies across variables of education, sector, industry and type of work.

Table 3 here

Table 3 also documents varied and uneven disparities across occupation i.e., presence of job discrimination between male and female worker. The negative coefficients signify an advantage for female workers, and this is visible at middle and low skilled occupations (NCO 5 and below). However, an advantage to male workers for both regular and casually employed in occupations requiring high and middle to high skills (NCO 1 to NCO 4), and also low skill (NCO 9). Interestingly, despite the presence of advantage to female workers in certain occupations, the absolute advantage is not very significant. The regular sector contributes more towards inequality as compared to the casual sector, which is contrary to the popular perception of higher wage inequalities and discrimination in casual employment.

The increase in wages with each additional educational level is quite high for highschool against graduate, showing an inflated contribution of middle level educated workers as part of casual employment, since our data considers both regular and casual workers. The summary statistics of the independent variables are presented in Appendix Table 1.

Table 4 here

6.3. Empirical Results: The Blinder Oaxaca Decomposition

Table 5a gives results using the actual notations of E, C, U and D as given by Blinder-Oaxaca 1973 (see Notes 3). Along with portion of endowment and discrimination, an "unexplained component" of discrimination (U) is given. Results clearly indicate a high raw wage differential of 51.5 percent, which is divided into three portions of which the endowment is significantly low at 3.1 percent percent and a much higher indispensable discrimination (coefficient) is 37.9. The third component, or the interaction term is the "unexplained portion of the raw differential" is 10.5 percent. The results are a glaring witness to significantly large amount of discrimination against females in the Indian labour market.

Table 5b summarises endowment, discrimination and interaction components as a percentage of total difference in wage. Results indicate a negligible endowment component as compared to discrimination component. The endowment component is 3.59 percent as part of the total difference in the wage gaps. Nevertheless discrimination explains almost 94 percent of lower wages and interaction is 2.42 percent. However, difference in endowments maybe due to past discrimination that is difficult to measure directly. Comparing the results with similar literatute using NSS data for previous rounds, show a greater and increasing share of discrimination over the decades against female workers; with the share of unexplained difference- as part of total discrimination also increasing over the years (Lama & Majumder, 2018).

Table 5a here

Table 5b here

Table 6 examines the contribution of each individual independent variable to the wage gap. Here, decomposition results of endowment, coefficient (discrimination) and a third interaction components in the earnings function is shown. The positive numbers indicate advantage to male workers and negative numbers indicate advantage to female workers. Looking at levels of education, graduation and post graduation are significant in their effects on wage gaps. Females show an earning advantage of 5.79 percent and 5.65 percent at graduate and postgraduate levels of education. But this small contribution in favour of females is diminished by the large constant term (20.33 percent) favouring the male workers.

Age factor is observed to have a significant impact on gender discrimination. Also interesting observation is that gender discrimination is greater in regular sectors as compared to casual sector, and this is quite contrary to usually perceived phenomenon of discrimination for casual workers. The amount attributable to coefficients is greater for graduates, post graduates and regular workers, while the first two favour the female worker, the later is a significant duscrimination against the female workers.

Table 6 here

Differentiated wage rate across age, sector, type of work, level of education is noted. After education, the wage differentials are substantially greater for NCO divisions 7, 8 and 9 and favour the male workers, showing a more pronounced wage gap. Using the wage structure of the male worker, we find that 18.84 percent of the total difference is attributable to the regular sector. Within the regular wage structure, 0.08 percent difference is attributable to characteristics (or endowments) and 16.49 percent is attributable to discrimination. An unexplained part of the wage differential is 2.26 percent. There is a marginal favourable treatment of female workers in NCO 2 (Professionals) and NCO 3 (Technicians and Associate Professionals), the adjusted differential of 0.12 percent and 0.01 percent respectively shows a miniscule earning advantage favouring the female workers in these divisions. Within the occupational divisions, there seems to be highest inequalities and observed significant discrimination at NCO 7 (Craft and Related Trade Workers) accounting for 7.83 percent of total wage differential.

7. Discussion

Our results have shown that across most variables the discrimination is greater than endowment, even though we cannot say the that unexplained portion was adequately discriminatory. This may be because our data does not take into account the human capital differences between workers in the Indian labour market. Many women, for example, remain excluded from the labour force given their added responsibilities for caring and other household obligations (Kingdon, 1998; Agarwal, 2013). The exceptions are urban sector where the discrimination componet is negative and favours the female and middle to higher levels of education, where both endowments and discrimination components are negligible but favour the female worker. Our findings concur with some other recent studies analysing gender gaps (see Lama & Majumder, 2018; Balakarushna et al., 2019), which is suggestive of the somewhat similar situation for Indian females in the workforce. Interestingly, during 1999-00 to 2009-10, gender wage gaps reduced slightly from 58.9 percent to 52.1 percent, where a larger gap was attributed due to unexplained components. However, post that explained portion has been reduced and unexplained portion has been rising, suggesting labour market favouring men.

Theil results indicate that the gender inequalities were greater in urban areas than in rural ones and interestingly, we see a higher inequality for regular female workers than for casual that may be attributed to a prevalence of substantially lower wages in the first place. Decomposition results show a stark inequality in the composition of male and female workers. And that even among those employed as regular workers, 71 percent female workers have no written job contract and more than half are not eligible for paid leave. Earnings function results show that higher education is a useful asset for women who show increasing returns than males at each subsequent level of education. Blinder Oaxaca sheds light on prevalent discrimination against women in the Indian labour market. Where the discrimination componenet explained for 94 percent and endowment component is observed at 3.59 percent of the total wage gap.

India has achieved higher growth rates since liberalisation, however this growth has come with reduced formalisation of the labour sector where a large number of workers work under exploitative and unsafe working conditions deprived of social securities or benefits. Inequalities in the labour market are reflected also in the form of unequal wages and discriminatory labour practices significantly based on gender (Balakarushna et al., 2019). Such discriminatory practices are linked to social and religious practices. Findings from this paper suggest wage disparities that is caused by gender discrimination and such gaps are persistently seen across formal and informal sectors and rural and urban areas. Such disparities are not just seen in wages but also as different working conditions and even as mode of payment for the work done (Das, 2012). Women have been paid much lower than the male workers with a wage differential found slightly more in the urban areas than rural as suggested in this paper and such findings are consistent with those in later years also (Chatterjee et al., 2015; Dasgupta & Verick, 2016; Mehrotra, 2020). Such barriers discourage women to join the labour force and even continue or grow in their career paths. Even though findings of this paper suggest inequalities and large gaps during the year 2011-12, not much has changed in the Indian labour market even in the present day (PLFS, 2017 - 2018). Women continue to earn less and the female labour force participation has been declining (Sundari, 2020). Labour participation had in fact fallen from 23.3 percent during 2009-10 to a low of 22.5 by the 68th round of 2011-12. Female participation has fallen by as much as 14 percent between 2003 and 2013 (Andres at al., 2017). A very high number of Indian women find themselves contributing to house-work and attending to domestic duties. In 2011-12, 35.3 percent of rural women and 46.1 percent of urban women attended to house-work and domestic duties. According to the National Sample Survey Office 68th round, about 64 percent of the women had no choice in taking up unpaid care-work where no other member of the "house was able to carry such domestic duties."

Policies have been adopted to increase female participation not only in terms of better access to the labour market but also to maintain such participation. The 2017 Amendment of the Maternity Benefit Act (1961) aims to provide beneficial entitlements to women, where the maternity leave has been increased from 12 to 26 weeks. Research has however found that around 48 percent of women discontinue work after completing their maternity leave. Providing facilities such as creche and child care need awareness and sensitivity towards understanding "gender-specific" issues that women face. Another improvement has been seen as achieving a significant increase in gross enrollment ratios for girls in primary and secondary education. However, such improvements have not materialised in terms of better participation and better pay for work, that reflect a deep rooted gender bias that expects domestic duties as sole responsibility of a woman (ILO, 2013; ILO, 2018). Some findings suggest that the nature of economic growth could not create a higher number of employment opportunities for women (Verick, 2018). To add to this, increase in preferences to continue higher education and even an overall increase in household income can be seen as reduced participation in the labour force.

Under the government's National Rural Drinking Water Programme and Pradhan Mantri Ujjwala Yojna programme women have spent a lesser number of hours in domestic work such as cooking and fetching water and more time on paid work. Such policies are welcome but will require long-term seriousness and effective use of available funds with better management. In reality various policies are left unenforced by employers. Such as the Mahatma Gandhi National Rural Employment Guarantee entitles free child care facilities to be provided by the employers, which are left unenforced.

At many occasions it is observed that low investments in education, or in poor quality education, difficulties in accessing higher education, even low investment in adequate nutrition and health for girls from an early age result in a 'pre-labour market discrimination', overall termed as 'lower social capital' (Das & Dutta 2007). As noticed earlier, large coefficient differential observed in case of most variables, suggest a discriminatory attitude towards women that has existed for generations and encompassed centuries of unfavourable status of females in the economic and social structure of our country. It is otherwise documented in literature that unequal labour market outcomes are stemming from some discrimination in the past that has limited the earnings and maintained deprivation for women workers (Das, 2012). The findings provided by these decomposition provide important insights into prevalent discrimination in education, sector, ocupation and type of work.

The Sustainable Development Goal 8 deals with the creation and sustenance of 'productive employment' that emphasises achieving equal and sustainable employment for both men and women along with “equal pay for work of equal value”. In context of present Indian scenario, Goal 8 therefore calls for sincere efforts for improving access to labour market through training programs, creation of skills development programs specially designed for women that incorporates dealing with complexities such as child care, maternity benefits, providing transportation and even safety that otherwise create barriers for women to access the labour market and newer opportunities to work and grow. Putting awareness about the highly discriminatory and biased Indian labour market at the core of a long grained thought process which discourages distribution of unpaid or care work and sees it primarily as a ‘women’s job’. The discourse on women’s inclusion in the labour market where she is provided an equal and respectable position in work and pay, requires elimination of the ‘wage penalty’ that women in general end up paying.

Tables

Table 1: Gender wage inequality using 90/10, 90/50 and 10/50 quantile ratios of average daily wage (2011- 2012)

	p90/p10	*p90/p50*	*p10/p50*
All Observations	8.889	3.810	0.429
Rural	4.762	2.381	0.500
Urban	10.417	4.167	0.400
Public	10.714	2.143	0.200
Private	5.476	2.465	0.450
Regular	10.000	3.846	0.385
Causal	3.500	1.739	0.497

Source: Author's own calculations based on NSS 2011-12 data.

Table 2: The Theil Decomposition of Wage Disparity based on Gender (within and between components)

Social Group	Employment Share (%)	Mean Wage	Gini index	Theil index	Within Group (%)		Between Group (%)	
Female	21.53	179.17805	0.53709	0.59316				
Male	78.48	268.84459	0.48136	0.45736				
Total Inequality			0.49949	0.49014	0.47835	97.59	0.01179	2.41
Rural Female	23.01	113.08278	0.38934	0.33674				
Rural Male	77.00	184.81223	0.38856	0.30669				
Total Inequality			0.40286	0.32894	0.31134	94.65	0.01760	5.35
Urban Female	18.97	317.86908	0.56114	0.55490				
Urban Male	81.03	406.96716	0.48677	0.43498				
Total Inequality			0.50224	0.45774	0.45352	99.08	0.00422	0.92
Private Female	21.25	134.06220	0.45462	0.47654				
Private Male	78.75	209.70280	0.41736	0.38362				

Total Inequality			0.43505	0.41122	0.39729	96.61	0.01392	3.39

Public Female	23.09	414.20512	0.51040	0.44092				
Public Male	76.91	611.58205	0.39106	0.27565				
Total Inequality			0.42169	0.31517	0.30357	96.32	0.01159	3.68

Regular Female	19.43	307.71816	0.55286	0.53682				
Regular Male	80.57	417.07557	0.47146	0.39873				
Total Inequality			0.48931	0.42595	0.41959	98.51	0.00636	1.49

Casual Female	23.28	89.28698	0.26993	0.12206				
Casual Male	76.72	138.44427	0.25659	0.11261				
Total Inequality			0.27527	0.12865	0.11416	88.74	0.01449	11.26

Source: Authors own calculations based on NSS 2011-12 data.

Table 3: Earnings Function OLS Results in Regular Salaried and Casual Workers Segregated by Gender (2011- 12)

	Males				**Females**			
	coeff	std err	t-value	P>|t|	coeff	std err	t-value	P>|t|
Age	0.024773	0.001524	16.26	0.00	0.013878	0.003470	4.00	0.00
Agesq	-0.000198	0.000021	-9.54	0.00	-0.000096	0.000047	-2.05	0.04
Bprim	-0.009764	0.008702	-1.12	0.26	0.068213	0.020210	3.38	0.00
Prim	0.020245	0.007850	2.58	0.01	0.050584	0.019270	2.62	0.01
Secon	0.156918	0.008394	18.69	0.00	0.221950	0.025026	8.87	0.00
Hsc	0.215699	0.010639	20.27	0.00	0.428002	0.031406	13.63	0.00
Grad	0.574489	0.011433	50.25	0.00	0.943504	0.026835	35.16	0.00
Diploma	0.491060	0.016828	29.18	0.00	0.830421	0.043580	19.06	0.00
Postgrad	0.805547	0.015551	51.80	0.00	1.153291	0.032156	35.87	0.00
NCO_1	0.520062	0.047406	10.97	0.00	0.233303	0.099552	2.34	0.02
NCO_2	0.490435	0.047172	10.40	0.00	0.436872	0.099418	4.39	0.00
NCO_3	0.236435	0.046974	5.03	0.00	0.225496	0.099681	2.26	0.02
NCO_4	0.196814	0.047008	4.19	0.00	0.097898	0.101664	0.96	0.34
NCO_5	0.032000	0.046213	0.69	0.49	-0.133924	0.098781	-1.36	0.18

NCO_6	-0.104214	0.046501	-2.24	0.03	-0.240565	0.098280	-2.45	0.01
NCO_7	0.142181	0.045659	3.11	0.00	-0.146047	0.097473	-1.50	0.13
NCO_8	0.205834	0.046037	4.47	0.00	-0.103308	0.099511	-1.04	0.30
NCO_9	-0.026188	0.045446	-0.58	0.56	-0.094254	0.096761	-0.97	0.33
Public	0.473425	0.008291	57.10	0.00	0.354835	0.018472	19.21	0.00
urban	0.175490	0.006233	28.15	0.00	0.211325	0.015731	13.43	0.00
Regular	0.214137	0.007478	28.63	0.00	0.007714	0.017548	0.44	0.66
_cons	4.137947	0.052505	78.81	0.00	4.033239	0.114095	35.35	0.00
R-squared	0.5157				0.4662			
Adj- R2	0.5155				0.4653			
Observations	50,746				13,178			

Source: Author's own calculations using NSSO data 2011-1

Notes*: p > 0.10 = insignificant variable ; 0.01 < p < 0.05 = significant at 90 percent level of confidence; 0.01 < p < 0.05 = significant at 95 percent; p < 0.01 = significant at 99 percent level of confidence.*

Table 4: Average Rate of Return on Education for males and females (2011-12)

	Males (%)	Females (%)
Prim	0.40	1.01
Secon	4.56	5.71
Hsc	2.94	10.30
Grad	11.96	17.18
Postgrad	11.55	10.49
Diploma (after HSC)	13.77	20.12

Source: Author's own calculation using NSS data 2011- 12

Note*: The rate of return is calculated as relative to the previous level of education (additional years of schooling is taken to estimate the return on education), the figures are not absolute terms. The levels of education are at par with the standard years used in existing literature. The omitted category of dummy variable is for workers who are illiterate or have less than 2 years of formal schooling/ or less than 2 years of formal education. We consider below primary education for those individuals who have not completed below primary or have less than 4 formal years of schooling.*

Additional year of schooling is considered as follows. 05 for primary; 03 for secondary; 02 for HSC; 02 for diploma; 03 for graduation and 02 for post graduation.

Table 5a: Summary of the Blinder-Oaxaca Decomposition Results (fig. In percentages)

Components of Decomposition	Males vs Females
Amount attributable:	41.0
- due to endowments (E):	3.1
- due to coefficients (C):	37.9
Shift coefficient (U):	10.5
Raw differential (R) {E+C+U}:	51.5
Adjusted differential (D) {C+U}:	48.4
Endowments as % total (E/R):	6.0
Discrimination as % total (D/R):	94.0

Source: Author's own calculations based on NSS data 2011-12

Table 5 b: The Blinder- Oaxaca Decomposition Results Components as a percentage of Total Difference

Components of Decomposition	Males vs Females	%
Due to endowment	0.01851	3.59
Due to coefficients	0.48408	93.99
Due to interaction	0.01246	2.42
Total Difference	0.51505	100.00

Source: Author's own calculations based on NSS data 2011-12

Table 6: Relative contribution to decomposition using different variables

	Endowments	%	Coefficients	%	Interaction	%	Total Difference
Age	-0.011236	-2.18	0.386804	75.10	-0.008821	-1.71	71.21
Agesq	0.004923	0.96	-0.140292	-27.24	0.005241	1.02	-25.27
Bprim	0.000777	0.15	-0.007314	-1.42	-0.000889	-0.17	-1.44
Prim	0.001474	0.29	-0.003308	-0.64	-0.000884	-0.17	-0.53
Secon	0.013926	2.70	-0.004182	-0.81	-0.004081	-0.79	1.10
Hsc	0.013861	2.69	-0.009256	-1.80	-0.006876	-1.33	-0.44
Grad	0.005707	1.11	-0.033313	-6.47	-0.002232	-0.43	-5.79

Diploma	0.004139	0.80	-0.007155	-1.39	-0.001691	-0.33	-0.91
Postgrad	-0.014510	-2.82	-0.018885	-3.67	0.004375	0.85	-5.63
NCO_1	-0.002758	-0.54	0.013719	2.66	-0.003389	-0.66	1.47
NCO_2	-0.005227	-1.01	0.003267	0.63	-0.000641	-0.12	-0.51
NCO_3	-0.001115	-0.22	0.000599	0.12	-0.000054	-0.01	-0.11
NCO_4	0.001515	0.29	0.003000	0.58	0.001531	0.30	1.17
NCO_5	-0.002475	-0.48	0.009759	1.89	0.003066	0.60	2.01
NCO_6	0.007745	1.50	0.011912	2.31	-0.004390	-0.85	2.96
NCO_7	-0.006903	-1.34	0.033618	6.53	0.013623	2.65	7.83
NCO_8	-0.005101	-0.99	0.014331	2.78	0.015263	2.96	4.76
NCO_9	0.006524	1.27	0.033584	6.52	-0.004711	-0.91	6.87
Public	-0.004926	-0.96	0.019098	3.71	-0.001646	-0.32	2.43
urban	0.011730	2.28	-0.011566	-2.25	-0.001989	-0.39	-0.35
Regular	0.000436	0.08	0.084949	16.49	0.011657	2.26	18.84
constant	0.000000	0.00	0.104708	20.33	0.000000	0.00	20.33
Subtotal	0.018507	3.59	0.484078	93.99	0.012463	2.42	100.00

Source: Author’s own calculations based on NSS data 2011-12

Appendix Table 1

Variables	Description of the Variables	Persons		Male		Female	
		Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
lwage	Logarithm of daily wage (in rupees)	5.092916	0.8540266	5.203781	0.8089961	4.688734	0.891212
Age	Age in years	34.86678	10.75851	34.69251	10.80917	35.50212	10.54779
agesq	Age squared	1331.436	789.1122	1320.406	792.179	1371.648	776.5325
<Primary	if completed below primary education=1; 0 otherwise	0.1027378	0.3036184	0.1051904	0.3068017	0.093796	0.2915557
Primary	if completed primary education=1; 0 otherwise	0.131901	0.3383857	0.1381715	0.3450833	0.1090405	0.3117018
Secondary	if completed secondary education=1; 0 otherwise	0.1135371	0.3172507	0.1270431	0.3330245	0.064298	0.2452924
HSC	if completed higher secondary=1; 0 otherwise	0.0690117	0.2534761	0.0759827	0.264973	0.0435975	0.2042056
Grad	if completed graduation=1; 0 otherwise	0.0950231	0.2932491	0.096325	0.2950394	0.0902765	0.2865884
Diploma	if completed diploma/ certificate course=1; 0 otherwise	0.0249938	0.1561073	0.0260665	0.1593348	0.0210829	0.1436661
Postgrad	if completed post graduation=1; 0 otherwise	0.0444341	0.2060592	0.041726	0.1999643	0.0543073	0.2266317
NCO_1	if belongs to NCO1=1; 0 otherwise	0.0385665	0.1925609	0.0360223	0.1863474	0.047842	0.2134398
NCO_2	if belongs to NCO2=1; 0 otherwise	0.0516018	0.2212234	0.0490263	0.215925	0.0609912	0.2393233
NCO_3	if belongs to NCO3=1; 0 otherwise	0.0508742	0.2197425	0.0498103	0.217555	0.0547528	0.2275058
NCO_4	if belongs to NCO4=1; 0 otherwise	0.042473	0.2016673	0.0458035	0.2090607	0.0303312	0.1715035
NCO_5	if belongs to NCO5=1; 0 otherwise	0.0733198	0.2606628	0.0772979	0.2670662	0.0588169	0.2352907
NCO_6	if belongs to NCO 6=1; 0 otherwise	0.0620961	0.2413319	0.055166	0.2283063	0.0873612	0.2823744
NCO_7	if belongs to NCO 7=1; 0 otherwise	0.1537292	0.3606918	0.1639031	0.3701913	0.116638	0.3210006
NCO_8	if belongs to NCO 8=1; 0 otherwise	0.0851012	0.2790344	0.0957285	0.2942215	0.0463571	0.2102652
NCO_9	if belongs to NCO 9=1; 0 otherwise	0.4390836	0.4962792	0.4241851	0.4942235	0.4933995	0.4999754
Public	if working in public sector=1; 0= private sector	0.1501514	0.3572225	0.1471631	0.3542719	0.1610458	0.3675871
Urban	if working in urban area=1; 0= rural area	0.366312	0.4817999	0.3782602	0.4849578	0.3227524	0.4675466
Regular	If regular worker=1; 0= casual worker	0.4558473	0.4980506	0.4680031	0.4989801	0.4115304	0.4921296

Source: Author's own calculations based on NSS data 2011-12

Notes*: The sample consists of individuals aged 15 - 59 in the NSSO (2011-12). Standard deviations are not reported for dummy variables.*

Endnotes

1. The NSS defines LFPR as the number of working age women in the age group of 15 to 59, either employed or available for employment, i.e., looking for work.
2. Classification of Occupations, dummy variable groups are: (for NCO 1) if a person is occupied in Legislators, Senior Officials, Professionals and Associate Professionals then 1; otherwise 0. (for NCO 2) If a person is occupied in/as Clerks, Service Workers, Shop and Market Sales Workers, Market Oriented Skilled Agri and Fishery Workers, Craft and Related Trade Workers, Plant and Machinery Operators and Assemblers then 1; otherwise 0. (for NCO 3) if a person is occupied in/as Subsistence Agri and Fishery work, Elementary Occupations and Work not classified by occupations then 1; otherwise 0.
3. The results of decomposition are as per Blinder (1973) and his original components that use E, C, U and D. E is the "endowment component" of the decomposition which is the sum of the coefficient vector of the regressors of the high-wage group multiplied by the difference in group means between the male and female for the vector of regression. C is the "coefficient component" which is calculated as the total of the group means of female and the difference between the regression coefficients of male and female groups. U is the "unexplained component" of the differential. And D is the "portion of difference because of discrimination" (C + U); the total difference is E + C+ U.
4. Ben Jann (2008) has introduced a STATA command "oaxaca" on implementing the Blinder and Oaxaca (1973) decomposition. This decomposition involves splitting the

total gap between wages of two sub-groups, such as men and women, into explainable and unexplainable components.

5. Codes assigned are not the same as average years of education. These codes as mentioned in the unit level data of NSS 2011-12, correspond to a level of education.

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