Gender-based Wage Differentials in India: Evidence Using a Matching Comparisons Method[1]

Tushar Agrawal
Associate Fellow
National Council of Applied Economic Research (NCAER)
Parisila Bhawan, 11- Indraprastha Estate, New Delhi – 110002, India
Email: tagrawal@ncaer.org

Reeve Vanneman
Professor
Department of Sociology, University of Maryland
College Park, MD 20742, USA
Email: reeve@umd.edu

Abstract

This paper examines gender wage differentials in India using the matching comparison methodology proposed by Ñopo (2008). This method is a non-parametric alternative to the standard Blinder-Oaxaca decomposition method. The method considers the problem of gender differences in the supports and allows the decomposition of the total wage gap into four components. Three of the components can be attributed to the existence of differences in individual's characteristics while the other is the unexplained part of the gap. The analysis is carried out using the nationally representative India Human Development Survey. We find a large wage gap that is more pronounced in rural areas than in urban. In both sectors, differences in individuals' characteristics explain a small proportion of the total wage gap. Further, occupational characteristics play an important role in explaining the wage differential. A large part of the gap remains unexplained which suggests within-occupation labor market discrimination against women.

Keywords: Gender wage gap; Discrimination; Matching comparison; Non-parametric; Wage decomposition; India

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1. Introduction

Females generally have lower average wage rates than their male counterparts. Despite substantial improvement in women's education and rising participation in the labor market, the gender wage gap has remained substantial in many countries (Chen et al. 2013). Though the gap exists in almost all countries, its size varies by country. Rising female labor force participation in many countries has been accompanied by an increase in their earnings (Gunderson 1989). If the marketable skills of working women increased relative to those of men, one may anticipate a decline in the gender wage gap (O'Neill and Polachek 1993).

Birdsall and Fox (1985) discuss various nondiscriminatory causes of the male-female wage differential. The most important one is due to differences in personal characteristics of men and women, especially the amount of human capital these groups possess. A second reason is women may be less geographically mobile than men and as a consequence more likely to accept jobs for which they are overqualified. A third reason is occupational gender segregation or a segmented labor market. If women are restricted to a relatively few occupations, this segregation may result in 'monopsonistic exploitation'.[2] Another reason of the differential could be due to the possibility of differences in cost-of-living across regions vis-à-vis the locational distribution of males and females.

Household gender roles may affect gender wage differentials for two reasons (Hersch 1991). First, if women support most household and child-care duties, their labor market experience may be more intermittent, and they are likely to work fewer total years than men. Thus, women acquire less work experience and have less incentive than men to undertake human capital investment such as firm-specific training. Employers, too, have less incentive to provide training for female workers whom they expect may leave for family duties. Second, household responsibilities (the "second shift") may reduce the amount of physical energy available for market work, and therefore may reduce worker productivity.

Most empirical studies on wage discrimination in India have found women earn significantly lower wages than men. Among social groups, scheduled castes and scheduled tribes also earn substantially lower wages. Deininger et al. (2013) focus on wage discrimination in informal labor markets, an issue largely neglected in the Indian literature despite the fact that informal markets are the main destination for the poorest section of the population. Their results suggest that gender wage discrimination is larger in informal labor markets than in formal labor markets. In casual labor markets, 50% to 68% of the gender wage gap can be attributed to discrimination. Further, they find that discrimination is more pronounced in the agriculture sector than the non-agriculture sector. About 45% to 68% of the gender gap in agriculture can be attributed to discrimination.[3]

[2] Monopsonist exploitation is a situation when a firm is the only (or at least the main) buyer of workers from labor market. It enables firms to exploit workers by setting lower wages and employing fewer workers than in a competitive market.

[3] The same estimates for the non-agriculture sector were insignificant.

The case of India is of particular interest because the gender wage differential is quite substantial. However, there is also evidence that the gap is declining over time (Bhaumik and Chakrabarty 2008). The topic requires periodic re-examination especially as new methods arise for evaluating the components of the differential. The paper uses a non-parametric wage decomposition method proposed by Ñopo (2008). This decomposition method uses matching comparisons for explaining gender differences and emphasizes the role of the differences in observable human capital characteristics. Using this methodology, all men and women are matched on the same combination of observable characteristics and wage gaps are recomputed for the matched groups.

The paper draws on the Ñopo methodology to study the gender wage differential and its components in India. The method helps us to infer to what extent observed differences in wages between men and women can be explained by differences in observable characteristics. It also allows us to analyze how much of the wage gap is explained by the outcomes of men and women outside of the common support. [4] To the best of our knowledge, no other study in India on wage differential has explicitly controlled for the common support. Therefore, the paper also tries to fill this gap in the Indian context. The analysis in the paper is based on a nationally representative dataset- India Human Development Survey (IHDS), which was conducted during 2004-05.

The rest of the paper is organized as follows. The next section discusses the dataset used in the paper. Section 3 lays out the non-parametric decomposition method. Section 4 discusses the results in detail. The last section offers concluding remarks.

2. Data and Descriptive Statistics

2.1 Data

This paper utilizes household data from the India Human Development Survey (IHDS). In the first wave of fieldwork (2004-05), a sample of 41,554 households was surveyed enumerating 215,754 individuals. The IHDS is a nationally representative survey of the population across all states and Union Territories of the country except the Andaman and Nicobar Islands and the Lakshadweep.[5] The survey has detailed demographic information (e.g., age, gender, marital status, household size, religion, social group, sector and place of residence) and socioeconomic position (e.g., land ownership, educational attainment, occupation and industry, type of job, and wages and earnings) among several other characteristics.

2.2 Variables

In the analysis, we use the following variables:

Age: Age of an individual in years.

[4] The common support refers to the region where the supports of the distributions of characteristics for males and females completely overlap.

[5] See Desai et al. (2010) for the survey sampling and more information about the survey.

Education: Education of an individual is grouped in one of the following categories: (i) Illiterate or below primary (0-2 years), (ii) Primary (3-5), (iii) Middle (6-8), (iv) Secondary (9-10), (v) Higher secondary (11-12), and (vi) Graduate (above 12 years).

Marital status: Married and unmarried. Married group includes married, divorced and widowed individuals.

Social groups: Scheduled castes, scheduled tribes, other backward classes (OBCs), and others. The last group 'others' includes all forward castes.

Religion: Hindus, Muslims, and others. 'Others' includes Christians, Sikhs, Buddhists, Jains, Tribals, and other religions.

Sector of residence: Rural or urban.

Region: To capture regional variations, we group all the states of the country into four regions: Northern, Eastern, Southern, and Western.[6]

Occupational characteristics: In the dataset, occupations are recorded using the National Classification of Occupations-1968 (NCO-68) scheme at the two-digit level. We prefer to work with the broadest classification of occupations (at the one-digit level). We have seven occupational categories at the one-digit level: (i) Professional, technical and related workers (codes 0 and 1), (ii) Administrative, executive and managerial workers (2), (iii) Clerical and related workers (3), (iv) Sales workers (4), (v) Service workers (5), (vi) Farmers, fishermen, hunters, loggers and related workers (6), and (vii) Production and related workers, transport equipment operators and laborers (7, 8 and 9). Further, information on whether an individual is a casual worker or a permanent worker is also available in the dataset.

Earnings/wages: The earnings variable is hourly wage, obtained by dividing the total amount received during a year (or per day or month) by the number of days worked in a year and the number of hours an individual usually works in a day. The wage distribution is trimmed by 0.1 percent at both the ends of the distribution.

Workforce participation: Individuals working more than 240 hours in a year are considered part of the labor force.

In our empirical analysis, we consider only the wage earners aged between 15 to 65 years. The lower bound of the age group ensures that the individual is not a child laborer. We conduct a separate analysis for rural and urban workers.

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[6] The 33 states (and Union Territories) are grouped as follows. The northern region includes nine states: Chandigarh, Delhi, Haryana, Himachal Pradesh, Jammu and Kashmir, Punjab, Rajasthan, Uttar Pradesh and Uttarakhand. The eastern region consists of 12 states: Arunachal Pradesh, Assam, Bihar, Jharkhand, Manipur, Meghalaya, Mizoram, Nagaland, Orissa, Sikkim, Tripura and West Bengal. The southern region includes five states: Andhra Pradesh, Karnataka, Kerala, Pondicherry and Tamil Nadu, and the western region covers seven states: Chhattisgarh, Dadra and Nagar Haveli, Daman and Diu, Goa, Gujarat, Madhya Pradesh and Maharashtra.

2.3 Descriptive Overview

Table 1 shows personal and labor characteristics of the individuals aged 15 to 65 years, separately for rural and urban sectors.[7] Male and female educational distributions differ in both sectors. More than half of the rural female population has little or no education, though this proportion in the urban sector is relatively lower (27%). On the other side, the uneducated proportions for the male population are 30 percent in the rural sector and 13 percent in the urban sector. However, the gender disparities in education are not as substantial as we ascend across the educational ladder, particularly in the urban sector.

[Insert Table 1 near here]

The proportion of working male individuals in the rural sector is 82 percent and for females the same proportion is 57 percent. The corresponding figures in the urban sector are relatively low. In fact in case of females only 20 percent are in the workforce. There is substantial difference in hourly wages between men and women in both the sectors. On average, men earn 9.8 rupees per hour in the rural sector while women earn 5.3 rupees. The corresponding values in the urban sector are 20.8 and 14.4, respectively. Turning to occupational characteristics, permanent employment accounts for less than five percent of male employment and three percent of female employment in the rural sector whereas the same shares in the urban sector are 33 percent for men and 25 percent for women. It is worth emphasizing that in the rural sector the workforce is primarily dominated by agriculture whereas in the urban sector the workforce is more in production-related occupations. Women tend to engage in low-skill occupations in both sectors.

3. Methodology

Most studies on wage discrimination use the conventional Blinder-Oaxaca decomposition method (Blinder 1973; Oaxaca 1973). This decomposition method separates the proportion of the average gender wage gap into two components: an explained component and an unexplained component. The first can be attributed to differences in average wage generating characteristics between males and females (endowments effect), and the second can be attributed to differences in returns to individual characteristics across the two distributions (returns or price effect). The second component is often referred as the part of the wage differential due to discrimination in the labor market. This component also captures unobservable characteristics.

However, the Blinder-Oaxaca decomposition method has some shortcomings. Ñopo (2008) points out that there could be a problem of misspecification in the Blinder-Oaxaca decomposition due to differences in the supports of the empirical distributions of individual characteristics for males and females (referred as gender differences in the supports). This is because there could be combinations of individual characteristics for which it is possible to find men in the labor force, but not women and vice-versa. One cannot compare outcomes of men and women with such non-overlapping combinations of characteristics. The Blinder-Oaxaca method

[7] These estimates are generated using the population weights provided in the dataset.

does not recognize these differences in the supports since it allows estimating wage equations for *all* male and female wage earners instead of limiting the comparison only to those individuals with comparable characteristics. Thus, the method is implicitly based on an "out-of-support assumption", i.e., it assumes that the linear estimators of the wage equation are also valid out of the supports of individual characteristics for which they are estimated.

Ñopo (2008) proposes an extension of the Blinder-Oaxaca decomposition method using a non-parametric matching approach. This method does not require any estimation of the wage equation. The basic idea is to compare the wages of a female worker to the wages of male workers with the same observable characteristics. The method can be explained as follows.[8] We have two gender groups: males (*M*) and females (*F*). Let *Y* denotes their wages, and *X* is a vector of individual characteristics. The expected value of wages of males and females respectively is given by:

$$E[Y|M] = \int_{S^M} g^M(x) dF^M(x) \tag{1}$$

and

$$E[Y|F] = \int_{S^F} g^F(x) dF^F(x) \tag{2}$$

where S^M and S^F denote the support of the distribution of characteristics of males and females respectively. The functions F^M (.) and F^F (.) are the conditional cumulative distribution functions of individuals' characteristics, conditional on being male and female, respectively, and dF^M (.) and dF^F (.) are their corresponding probability measures. The functions g^M (.) and g^F (.) represent the expected value of wages, conditional on characteristics and gender: $E[Y|M, X] = g^M(X)$ and $E[Y|F, X] = g^F(X)$.

The wage gap (Δ) is defined as

$$\Delta \equiv E[Y|M] - E[Y|F] \tag{3}$$

Given that the support of the distribution of characteristics for males and females are different, each integral is split into two parts: within the intersection ($S^M \cap S^F$) and out of the common support ($S^F \cap \overline{S^M}$ and ($\overline{S^F} \cap S^M$).

$$\begin{aligned} \Delta = & \left[\int_{\overline{S^F} \cap S^M} g^M(x) dF^M(x) + \int_{S^M \cap S^F} g^M(x) dF^M(x)\right] \\ & - \left[\int_{S^M \cap S^F} g^F(x) dF^F(x) + \int_{S^F \cap \overline{S^M}} g^F(x) dF^F(x)\right] \end{aligned} \tag{4}$$

Ñopo (2008) shows that the above equation can be expressed as a sum of four elements:

$$\Delta = \Delta_X + \Delta_M + \Delta_F + \Delta_O$$

[8] Methodology and notations in this paper are taken paper from Ñopo (2008).

The first component is the part of the wage gap that can be explained by differences in distributions of characteristics of males and females on the common support. It is expressed as:

$$\Delta_x \equiv \int_{S^M \cap S^F} g^M(x) \left[\frac{dF^M}{\mu^M(S^F)} - \frac{dF^F}{\mu^F(S^M)}\right](x)$$

The second component is the part of the gap explained by the differences in characteristics between two groups of males: unmatched males and matched males (those who have characteristics that can be matched to female characteristics). It is given as:

$$\Delta_M = \left[\int_{\overline{S^F}} g^M(x) \frac{dF^M(x)}{\mu^M\left(\overline{S^F}\right)} - \int_{S^F} g^M(x) \frac{dF^M(x)}{\mu^M(S^F)}\right] \mu^M\left(\overline{S^F}\right)$$

This component is computed as the weighted difference between the expected wages of males out of the common support and the expected wages of males in the common support.

The third component is the part of the gap explained by the differences in characteristics between two groups of females: matched females (those who have characteristics that can be matched to male characteristics), and unmatched females. It is given as:

$$\Delta_F = \left[\int_{S^M} g^F(x) \frac{dF^F(x)}{\mu^F\left(\overline{S^M}\right)} - \int_{\overline{S^M}} g^F(x) \frac{dF^F(x)}{\mu^F\left(\overline{S^M}\right)}\right] \mu^F\left(\overline{S^M}\right) \quad (8)$$

This component is computed as the weighted difference between the expected wages of females in the common support and the expected wages of females out of the common support.

The fourth component is the unexplained part of the wage gap. It is expressed as:

$$\Delta_O \equiv \int_{S^M \cap S^F} [g^M(x) - g^F(x)] \frac{dF^F(x)}{\mu^F(S^M)} \quad (9)$$

Therefore, the overall wage gap can be decomposed into four additive components:

$$\Delta = (\Delta_X + \Delta_M + \Delta_F) + \Delta_O \quad (10)$$

The sum of the first three components is the portion of the wage gap that can be attributed to differences in observable characteristics.[9] The fourth component is the portion of the gap that can be attributed to differences in unobservable characteristics and discrimination.

The matching procedure used to estimate the four components involves the following steps. Step 1: Select one female (without replacement) from the sample, Step 2: Select all males having the same characteristics of the previously selected female, Step 3: Construct a synthetic individual with all the individuals selected in step 2, whose wage is equal to the average of all of the selected individuals and match the synthetic individual to the original female, Step 4: Put the observations

[9] It is worth noting that the second component (Δ_M) would disappear if all males can be matched to the females' population or all unmatched males earn, on average, the same average wages as much as the matched males. Similarly, the third component (Δ_F) would disappear if all females can be matched to the males' population or all unmatched females are paid, on average, the same average wages as the matched females.

of the synthetic male and the female in their respective new samples of matched individuals, and Step 5: Repeat the four steps until the original female sample is exhausted (Ñopo 2008).

However, it may be noted that the above method has two main limitations. First, matching variables should be discrete variables. Second, it suffers by the ‘curse of dimensionality’, i.e., the use of many matching characteristics lowers the chances of finding an adequate number of matched observations and hence the size of the common supports.

4. Results

4.1 Wages by educational level

We begin by discussing some important findings from the dataset. Figure 1 shows the log hourly wages for men and women (on the vertical axis) by educational level (on the horizontal axis). The figure indicates that the gender wage gap is more pervasive at low levels of education. However, as educational level rises the wage gap between men and women declines.

The figure also shows substantial rural and urban wage differences for both men and women. Also, in both areas and for both men and women, there is a sudden rise in wage rates after middle level of education. In particular, the wages of urban females change abruptly with higher education. This confirms a finding by Agrawal (2012) that returns to education in India after middle level of education increase sharply in both the rural and urban sectors.

[Insert Figure 1 near here]

Further, we plot the kernel density estimates of log hourly wage for men and women at low and high education levels separately for both the rural and urban sectors (Figures 2a - 2d). Less educated workers have education below the secondary level (up to middle level) while the highly educated sample comprises those who have secondary or beyond secondary education. The distance between densities of males and females’ wage distribution at any point represents the extent of the raw wage gap.

The plots indicate that the female distributions are more skewed towards the left than the male distributions. Female wages are lower than male wages, but the four plots show clearly different wage distributions. Figure 2(d) is of particular interest (highly-educated urban sector); the upper tails of male and female distribution coincide with each other. This suggests that the wage gap between men and women is low among the more educated, high wage earners in the urban sector.

[Insert Figures 2a-2d near here]

4.2 Gender wage differential: decomposition results

The decomposition results using the matching method are presented in Table 2, separately for the rural and urban sectors. We use seven specifications which have different sets of matching variables. In the first specification, we use only age as a matching characteristic. In the second, we add individuals’ educational level. In the third, we add marital status as another individual characteristic. In the fourth, we incorporate religion and social group. In the fifth, we additionally control for occupations of individuals. In the sixth, we consider all the previous characteristics and nature of employment. In the last specification, in addition to all the other matching variables, a regional control is also taken into account.

[Insert Table 2 near here]

The total gender wage gap (Δ) is 89.7 percent in the rural sector and 36.9 percent in the urban sector. The wage gap is measured as a percentage of the average female (hourly) wages so this suggests that men earn 89.7 percent (36.9 percent) higher hourly wages in the rural (urban) sector than women. As can be seen, the gender wage gap is considerably higher in the rural sector than in the urban.

As discussed, the raw wage gap is decomposed into four additive components: Δ_0, Δ_M, Δ_F and Δ_X. When we control only for age (specification 1), most of the wage gap remains unexplained in both the rural and urban sectors. Adding education explains a large part of the wage gap. The explained component increases form 1.6 percent of average female wages to 38.3 percent in the rural sector and from 2.6 percent to 17.2 percent in the urban sector. As noted earlier, females have relatively lower educational attainment than males so a large part of the reason for the gender wage gap is women's lower human capital.

Adding marital status (specification 3) and social characteristics (specification 4) does not change the unexplained component very much as men and women are quite similar on these characteristics.

However, controlling occupational characteristics (specifications 5 and 6) changes the explained and unexplained components substantially. A sizable workforce in India is employed in casual work. Therefore, accounting for this fact, we control for formality (casual or permanent occupation) in the sixth specification. In the full set (specification 7), a sizable portion of the wage gap remains unexplained (31.1 percent in the rural sector and 25.6 percent in the urban) by these observable characteristics. A large remaining share of the unexplained component indicates substantial wage discrimination against women in both rural and urban sectors.

As explained earlier, the matching approach provides two additional components: Δ_M and Δ_F – the proportions of the wage gap owing to male and female distributions outside the common support, that is, outside the overlapping portions of the distributions of matching characteristics. It is interesting to see the extent of these two components and how they vary across different specifications. In the first two specifications, almost all men and women are in the common support. Therefore, the two components Δ_M and Δ_F are very small. However, adding more controls results in increases in Δ_M. In fact, in the last two specifications, a large share of explained component is due to Δ_M. Male domination of the most lucrative occupational positions accounts for a good portion of the gender wage gap.

We note that in most of the specifications Δ_M is positive and Δ_F is either negative or zero. A positive sign on Δ_M indicates that unmatched males actually earn on average more than matched males, and a negative sign on Δ_F indicates that unmatched females earn more than matched females. In the rural sector, the extent of Δ_M remains very high (more than 30 percent) particularly in the last three specifications. This means that a large share (about 35 to 40 percent) of the wage gap can be explained because men reach certain combinations of employment characteristics that women fail to reach. In the urban sector too, this component plays a substantive role in explaining the gender gap. The negative values of Δ_F indicate that there are also some other well paid segments of the labor market to which women have access and men do not (Ñopo et al. 2011) but which pay better than average female wages.

As we add more variables in the control set, the proportions of individuals in the common support decline: it is more difficult to match men and women on multiple characteristics than on one or two. After adding occupational characteristics and region, the percentage of individuals in the common support drops substantially (specifications 5 to 7). In the urban sector for the full set of matching variables, only 16.9 percent of men and 41.4 percent of women are in the common support of distributions of observable characteristics.

4.3 Distribution of the unexplained gap

The matching approach allows an exploration of the distribution of the unexplained wage gap. Figures 3a and 3b show the magnitude of both the total and unexplained wage gaps along the wage distribution for the rural and urban sectors, respectively.[10] We use three different set of control variables (specifications 2, 4 and 6). The distributions of the unexplained gap using the first and second sets of variables closely follow each other in both the sectors. In the rural sector, the unexplained gap does not change very much along the wage distribution though it is somewhat lower at the bottom end. However, the total wage gap is also lower at the bottom end. In the urban sector, the unexplained gap tends to be higher at the bottom wage percentiles followed by a sharp decrease after the median. This pattern also holds for total wage gap. Adding occupational characteristics as matching variables (Set 3 in the figures) moves up the unexplained gap in the rural sector and moves down the gap in the urban sector for most percentiles of the distribution.

[Insert Figures 3a-3b near here]

Further, the wage gap distributions show very different patterns in the rural and urban sectors. In the rural sector, the total wage gap increases from the bottom end of the wage distribution to the upper end; in the urban sector just the reverse happens: the gap decreases from the bottom end of the distribution to the upper end in the urban sector. This indicates the presence of a glass-ceiling effect in the rural sector and a sticky-floor effect in the urban sector. This phenomenon is evident in Agrawal (2013). Overall our findings suggest evidence of labor market discrimination against females.

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[10] The unexplained gap is the wage gap between the representative male and female at each percentile of the wage distributions of males and females, respectively. This is computed using the matching samples, so the wage differences are those that remain unexplained after controlling for observable characteristics. We are grateful to Hugo Ñopo and Felipe Balcázar for helping us with Stata codes for plotting this figure.

4.4 Gender wage differential for casual and permanent workers

Finally, we examine the gender wage gap separately for casual and permanent workers. The results are reported in Table 3, again separately for rural and urban sectors. We observe that the gender wage gap is higher in the rural sector for both casual and permanent workers. It is also higher for casual workers in the urban sector. Nevertheless, the wage gap is very low for permanent workers in the urban sector. This is the most privileged part of the Indian labor market. Here, two components, Δ_M and Δ_F, play crucial roles in explaining the gender gap. Unlike other cases, these components have opposite sign, i.e., Δ_M is negative and Δ_F is positive. A negative sign on Δ_M indicates that those observable characteristics (e.g., occupations) that women fail to achieve are not associated with higher wages than those of matched men. A positive Δ_F component suggests the segregation of women into the labor markets where wages are below average (Ñopo et al. 2011). Additions of matching variables result in decreases in Δ_M and increases in Δ_F.

[Insert Table 3 near here]

The data show that the integration of both male and female permanent workers is quite good in the urban sector (Table 1). This is due to the fact that the permanent jobs' opportunities are more available in urban areas than in rural areas. Most permanent jobs in the urban sector are regular government or public jobs. Wages in these jobs remain more comparable for men and women so one can expect a smaller wage gap for permanent employees. We also find that even the wages of permanent workers without government jobs are comparable in the urban sector (results not reported).

On the other hand, the distribution of wages for casual workers in the urban sectors looks more like the distribution of wages for casual workers in the rural sector. It is the urban permanent sector that is distinctive in the urban labor market and that is the one area with much smaller gender wage gaps.

5. Conclusions and Policy Implications

This paper investigates male-female wage differentials for India using a non-parametric wage decomposition method. The method considers the differences in the supports (ranges) of the distributions of characteristics for males and females such as differences in education and occupation. The total wage gap is decomposed into four components. Three of them can be grouped to understand differences in individuals' characteristics – 'the explained component' – and the other part captures differences in unobservable characteristics –'the unexplained component'. We find that the wage gap is higher in the rural sector than in the urban sector and higher for casual workers than for permanent workers. It is the urban permanent sector that has the smallest gender wage gaps.

The decomposition results show a large part of the wage differential unexplained. This suggests evidence of labor market discrimination against women. We also note that occupational characteristics play an important role in explaining the gender wage differential. This is especially true in the rural sector and for casual urban employment.

Our findings have clear policy implications. There is a need to promote employment opportunities for females. However, raising the female participation is not only the crucial factor, the level of human capital and the composition of the workforce also matter. We have observed that the female participation rate is higher in the rural sector as compared to the urban sector, but the extent of the wage gap is higher in the rural sector. In the urban sector females have relatively higher educational attainment, and their representation in skilled occupations is also high. Therefore, access to education and good quality jobs for women in rural areas and in the urban casual sector are central policy considerations.

The Constitution of India already has the principle of "equal pay for equal work". In this connection, Article 14 of the Constitution of India declares that "the State shall not deny to any person equality before the law or equal protection of the laws within the territory of India". According to Article 39(d) "the State shall, in particular, direct its policy towards securing: that there is equal pay for equal work for both men and women". Further, the Equal Remuneration Act, 1976 aims to provide for the equal payment to male and female workers and for the prevention of gender discrimination at work. In this respect, the Act has two main provisions: (i) a duty of the employer to pay equal remuneration to men and women for same work or work of a similar nature, and (ii) no discrimination to be made while recruiting men and women workers.[11] This legislation needs to be followed more strictly at the workplace.

Finally, this study is based on a single wave of the survey that is the only wave of the survey available till date. Future research could analyze changes in the components of total wage gap using two waves of the survey. It will help in finding out whether discrimination in the Indian labor market is declining over time. An important related aspect – how child care activities affect female participation and their wages – has not been explored in developing countries. This issue needs special attention in countries like India given the country's low female workforce participation rate.

[11] Source: http://pblabour.gov.in/pdf/acts_rules/equal_remuneration_act_1976.pdf (last accessed on October 4, 2013).

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Tables

Table 1: Personal and Labor Characteristics by Gender

Variable	Rural		Urban	
	Male	Female	Male	Female
Age	34.6	34.4	34.3	34.0
	(14.2)	(14.1)	(13.7)	(13.6)
Educational Level:				
Illiterate & Below Primary	0.298	0.564	0.127	0.270
Primary	0.161	0.133	0.108	0.117
Middle	0.174	0.129	0.165	0.163
Secondary	0.217	0.113	0.264	0.209
Higher Secondary	0.090	0.042	0.149	0.115
Graduate	0.060	0.020	0.187	0.126
Marital Status (Married)	0.698	0.791	0.647	0.759
Social Group:				
Others	0.255	0.256	0.417	0.413
OBC	0.417	0.421	0.389	0.390
SC	0.233	0.231	0.168	0.170
ST	0.095	0.093	0.026	0.027
Religion:				
Hindu	0.835	0.833	0.779	0.774
Muslim	0.106	0.107	0.159	0.160
Others	0.059	0.060	0.063	0.067
Work Participation	0.817	0.566	0.705	0.198
Hourly Wage	9.79	5.34	20.81	14.44
	(9.80)	(5.37)	(18.97)	(17.08)
Permanent Job	0.097	0.042	0.333	0.245
Occupation:				
Professional	0.041	0.024	0.092	0.183
Administrative	0.005	0.001	0.036	0.010
Clerical	0.036	0.007	0.140	0.082
Sales	0.020	0.005	0.076	0.030
Service	0.033	0.036	0.088	0.213
Agriculture	0.456	0.739	0.061	0.143
Production	0.409	0.188	0.507	0.339

Note: Standard deviations appear in parentheses and are not reported for categorical variables.
Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.

Table 2: Results of the Gender Wage Gap Decomposition

Component	1	2	3	4	5	6	7
				Rural			
Total wage gap (Δ)	89.68	89.68	89.68	89.68	89.68	89.68	89.68
Δ_M	0.00	4.95	6.23	23.49	41.91	48.58	59.27
Δ_F	0.00	0.00	-0.24	-1.76	-6.13	-8.45	-11.87
Δ_X	1.64	38.34	37.97	23.50	18.01	14.53	11.21
$\Delta_M + \Delta_F + \Delta_X$	1.64	43.30	43.96	45.24	53.79	54.66	58.61
Unexplained gap (Δ_0)	88.04	46.38	45.72	44.44	35.89	35.02	31.07
% Male in common support	100.00	98.26	97.19	80.20	62.31	59.25	41.49
% Female in common support	100.00	99.99	99.72	97.29	92.03	89.67	79.01
				Urban			
Total wage gap (Δ)	36.92	36.92	36.92	36.92	36.92	36.92	36.92
Δ_M	0.00	1.03	0.03	-2.10	6.83	11.93	14.24
Δ_F	0.00	-0.01	-0.10	-2.35	-1.83	-1.77	-5.84
Δ_X	2.64	17.23	18.01	19.16	1.14	1.80	2.96
$\Delta_M + \Delta_F + \Delta_X$	2.64	18.25	17.94	14.71	6.14	11.96	11.36
Unexplained gap (Δ_0)	34.28	18.68	18.98	22.21	30.79	24.97	25.56
% Male in common support	100.00	98.09	96.17	69.56	40.28	33.78	16.90
% Female in common support	100.00	99.90	99.06	90.86	70.48	63.54	41.35

Notes: All the figures are in percentage term. Please refer to methodology section for description of components. Seven columns (1-7) represent different specifications: 1. Age; 2. Age and education; 3. Age, education and marital status; 4. Age, education, marital status, social group and religion; 5. Age, education, marital status, social group, religion and occupation categories; 6. Age, education, marital status, social group, religion, occupation categories and type of job; and 7. Age, education, marital status, social group, religion, occupation categories, type of job, and regions.

Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.

Table 3: Gender Wage Decomposition: Casual and Permanent Workers

Component	Rural					Urban				
	1	2	3	4	5	1	2	3	4	5
Casual Workers										
Total wage gap (Δ)	69.85	69.85	69.85	69.85	69.85	56.54	56.54	56.54	56.54	56.54
Δ_M	0.00	1.51	2.21	10.05	19.22	0.00	2.71	2.31	3.51	11.25
Δ_F	0.00	0.00	-0.01	-0.59	-3.01	0.00	-0.15	-0.47	-2.24	-6.88
Δ_X	-0.37	16.32	16.31	11.93	14.80	-0.41	11.21	10.46	10.51	3.71
Unexplained gap (Δ_0)	70.22	52.02	51.35	48.46	38.84	56.95	42.76	44.24	44.76	48.47
% Male in CS	100.00	98.03	96.91	80.81	65.62	100.00	96.96	93.61	62.50	39.78
% Female in CS	100.00	99.99	99.74	97.35	92.71	100.00	99.86	98.89	90.09	66.38
Permanent Workers										
Total wage gap (Δ)	55.38	55.38	55.38	55.38	55.38	5.19	5.19	5.19	5.19	5.19
Δ_M	2.06	4.64	1.80	3.37	-11.34	-0.02	-3.21	-4.66	-12.37	-20.10
Δ_F	0.00	0.44	-0.20	7.90	29.24	0.00	0.69	1.20	4.47	12.65
Δ_X	12.99	33.33	36.45	29.16	21.22	3.65	4.38	5.97	7.63	3.64
Unexplained gap (Δ_0)	40.33	16.98	17.34	14.95	16.26	1.56	3.32	2.69	5.47	9.01
% Male in CS	97.81	76.87	72.61	26.40	9.13	99.98	88.93	85.38	52.12	22.24
% Female in CS	100.00	99.18	93.85	63.11	29.92	100.00	98.98	96.54	75.93	55.70

Notes: All the figures are in percentage term. Please refer to methodology section for description of components. Five columns (1-5) represent different specifications: 1. Age; 2. Age and education; 3. Age, education and marital status; 4. Age, education, marital status, social group and religion; and 5. Age, education, marital status, social group, religion and occupation categories. CS denotes common support.
Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.

Figures

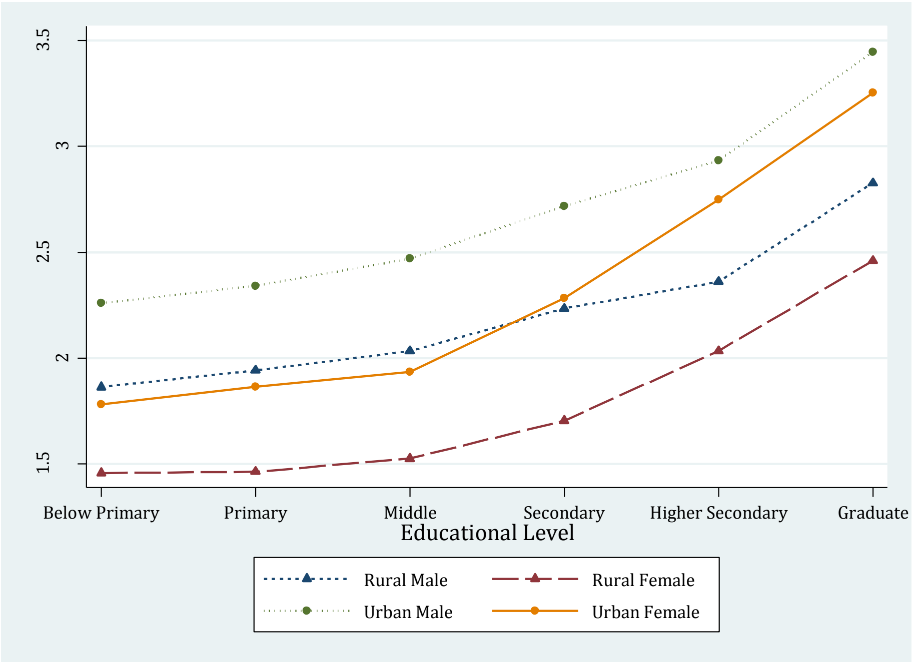


Figure 1: Log Hourly Wages for Males and Females by Educational Level

Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.

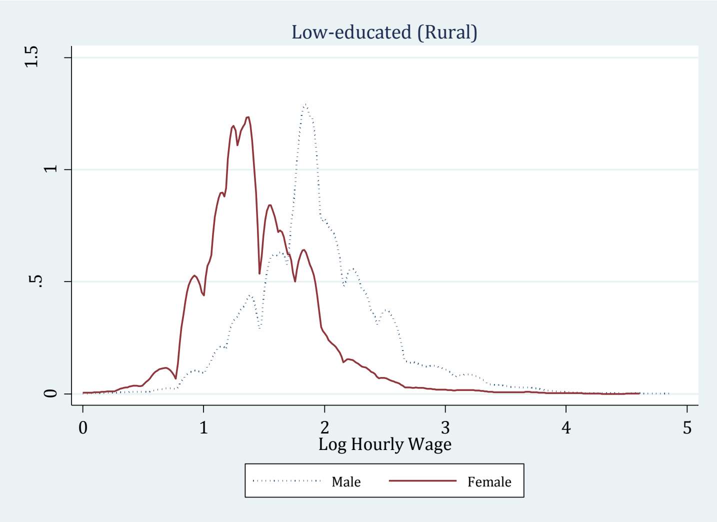
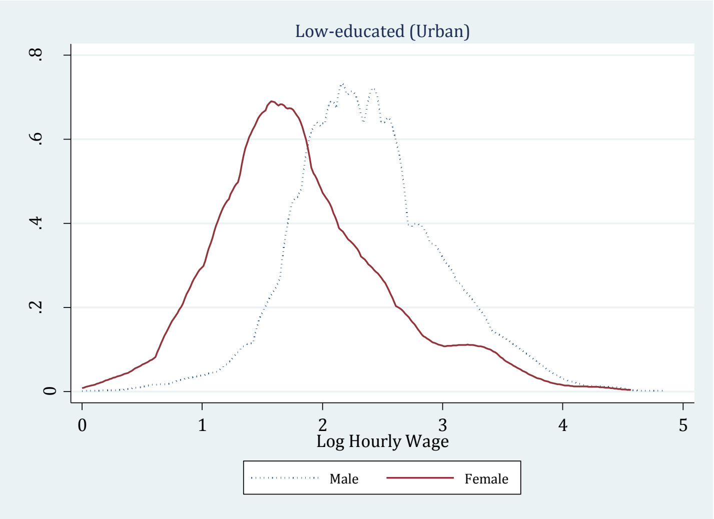


Figure 2(a)



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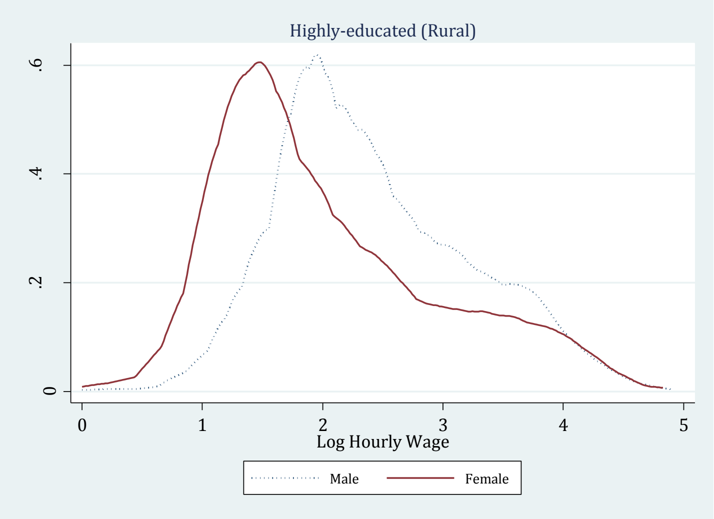

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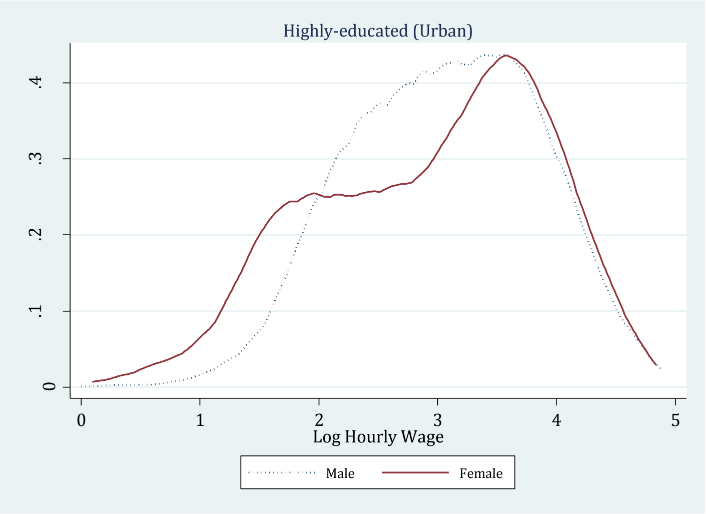

Figure 2(d)

Figures 2 (a) - 2 (d): Kernel Density Estimates of Log Hourly Wage for Males and Females by Education Group

Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.

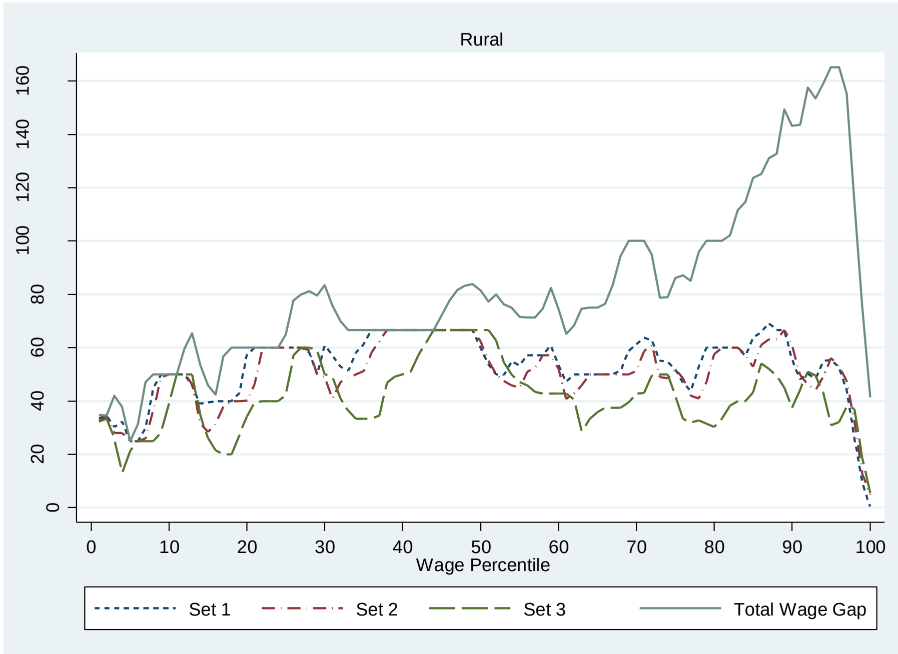

Figure 3(a)

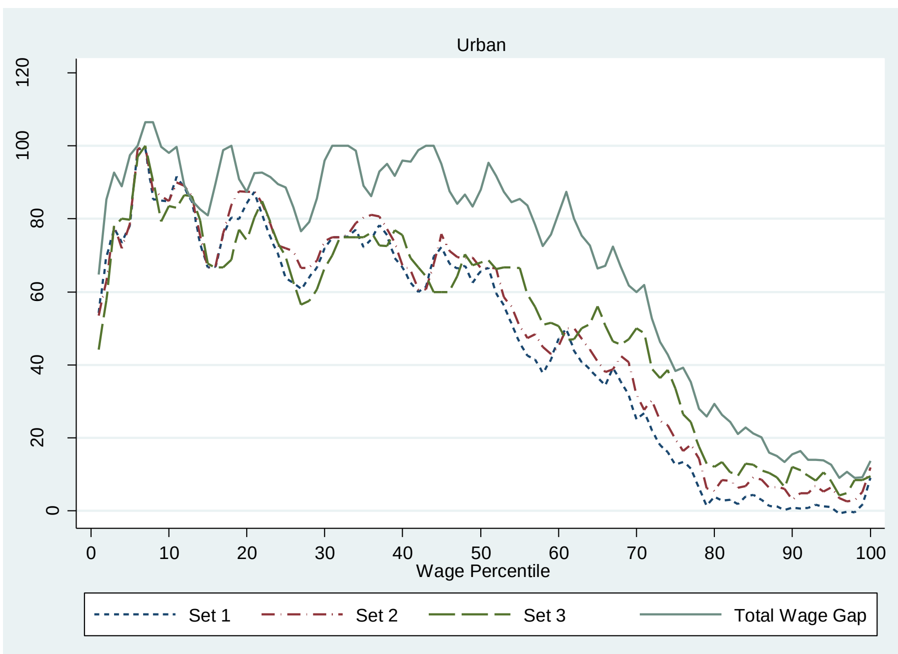

Figure 3(b)

Figures 3 (a) - 3 (b): Unexplained Gap and Total Wage Gap by Percentiles of the Wage Distribution of Males and Females

Notes: Unexplained wage gap across the wage distribution is plotted using four different sets of control variables. Set 1: Age and education, Set 2: Set 1+ marital status, social group and religion, and Set 3: Set 2+ occupational characteristics.

Source: Authors' calculations from IHDS (2005) for individuals in age group 15-65 years.