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Bad Karma or Discrimination? Male–Female Wage Gaps Among Salaried Workers in India

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SUMMARY

We use nationally representative data from the Employment–Unemployment Surveys in 1999–2000 and 2009–10 to explore gender wage gaps among Regular Wage/Salaried (RWS) workers in India, both at the mean, as well as along the entire wage distribution to see "what happens where". The gender log wage gap at the mean is 55% in 1999–2000 and 49% in 2009–10, but this change is not statistically significant. The Blinder–Oaxaca and the Machado–Mata–Melly decompositions indicate that, in both years, the bulk of the gender wage gap is unexplained, i.e., possibly discriminatory. They also reveal that over the decade, while the wage-earning characteristics of women improved relative to men, the discriminatory component of the gender wage gap also increased. In fact, in 2009–10, if women were "paid like men", they would have earned more than men on account of their characteristics. In both years, we see the existence of the "sticky floor", in that gender wage gaps are higher among low-wage earners and lower for high-wage earners. Over the ten-year period, we find that the sticky floor became "stickier" for RWS women. Machado–Mata–Melly decompositions reveal that, in both years, women at the lower end of the wage distribution face higher discriminatory gaps compared to women at the upper end.

1. Introduction

Satya Nadella, the CEO of Microsoft, in an interview in front of a prominent group of women IT professionals, said that women needed to trust "karma" if they don't get the pay raise they want. "It's not really about asking for a raise, but knowing and having faith that the system will give you the right raise".[1] The statement was widely criticized, leading to a quick apology from Nadella, but it brought to the fore a fundamental question about how labor markets function, especially toward members of disadvantaged and marginalized groups. Should such individuals "have faith" and hope for their rewards to improve? If labor markets do not recognize and appropriately remunerate their worth, is it just a case of bad luck, or of labor market discrimination?

The problem is not simply one of pay raises, but more broadly one of gender parity in wages, which is a ubiquitous feature of labor markets everywhere. This paper analyzes the issue of gender parity in wages by focusing on the evolution of male–female wage gaps for an emerging economy, India. We also decompose these wage gaps to understand patterns of gender-based labor market discrimination, both at the mean as well as along the entire distribution to understand "what happens where". Studies that decompose gender wage gaps along the entire wage distribution raise an important issue within the gender discrimination literature: do women face a "glass ceiling" or a "sticky floor"? We contribute to this literature by documenting that in India the gaps are higher for low-wage earners compared to high-wage earners, i.e., we have a "sticky floor" instead of a "glass ceiling" that characterizes most developed country labor markets.

We use nationally representative data from the Employment–Unemployment Schedule (EUS) of two large rounds of the National Sample Survey (NSS) for 1999–2000 and 2009–10, respectively in order to explore gender wage gaps among Regular Wage/Salaried (RWS) workers. We focus on this segment for two reasons. One, this is a segment of the workforce where jobs are presumed to be allocated on meritocratic lines. Two, part of the reason underlying low-reported labor force participation rates of women in developing countries like India is under-reporting, i.e., women underestimate and/or under-report their involvement in productive work.[2] This underestimation is likely to minimal among RWS workers. We exam-

[1] http://recode.net/2014/10/09/open-mouth-insert-foot-microsoft-ceo-tells-women-techies-to-trust-karma-on-pay-inequity/, accessed on 23rd November 2014.

[2] See Deshpande (2011) for a discussion of under-reporting.

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ine wage gaps at the mean as well as along the entire distribution. We then decompose the gaps into an "explained component" (due to gender differences in wage earning characteristics), and the "unexplained component" (due to gender differences in the labor market returns to characteristics); the literature treats the latter as a proxy for labor market discrimination. We perform the standard mean decomposition (using the Blinder–Oaxaca method, BO hereafter) and quantile decompositions (using Melly's refinement of the Machado–Mata decomposition method, MMM hereafter). We then evaluate changes in each of these over the ten-year time period. Our study presents the latest comprehensive empirical evidence on gender wage gaps and labor market discrimination in India. This is among the earliest studies of gender discrimination along the entire wage distribution for India and the first to focus on regular salaried workers.

Our main findings are as follows. There are significant gender gaps among RWS workers who constitute about 17% of the Indian labor force. The raw (unconditional) gender wage gap at the mean changes from 55% to 49% between 1999–2000 and 2009–10, but this change is not statistically significant. In both years, even after accounting for differences in observable characteristics, average female wages were less than for males. BO decompositions indicate that the bulk of the gender wage gap at the mean is unexplained, i.e., possibly discriminatory. While the educational and occupational attainment of women improved relative to men over the decade, the discriminatory component of the wage gap also increased. In fact, in 2009–10, if women were paid like men, they would have earned more than men on account of their superior characteristics.

Moving beyond the mean, for both years, male wages are higher than female wages across the entire wage distribution. In both years, the gender wage gaps are higher at lower deciles and decline thereafter. In 2009–10, the gap is highest at the first decile at 105%, and it declines to about 10% at the ninth decile, indicating the existence of the "sticky floor", in that gender wage gaps are higher at lower ends of the distribution and steadily decline over the distribution. This is true for all RWS workers, as well as separately for rural and urban workers. Using standard definitions, we find that the sticky floor became "stickier" for RWS women over the decade. Like the BO decomposition, the MMM decompositions also reveal that bulk of the gender wage gaps are discriminatory, and that the discriminatory component is higher at lower ends of the distribution.

The rest of this paper is organized thus. Section 2 contains a review of the literature; Section 3 explains the decomposition technique; Section 4 describes the data and presents gender differences in characteristics; Section 5 contains the regression and decomposition results; Section 6 discusses the findings in the larger context of gender discrimination; and Section 7 offers concluding comments.

2. A brief review of the literature

The overall literature on gender discrimination in India is vast, and covers a very broad array of disciplines and methodologies. Since our study is empirical, focused on the labor market and especially on wage gaps, we refer to the relevant literature here.

(a) Understanding gender wage gaps

In addition to clear and persistent differences in labor force participation rates, data reveal sharp gender wage gaps, the latter consistent with international experience. Mahajan and Ramaswami (2015) investigate the apparent paradox that gender wage gaps in agricultural wages are higher in south India, a region with more favorable indicators for women, compared to north India. They investigate whether this could be due to Ester Boserup's proposition, viz., that higher gender gaps in the south are due to higher female labor force participation rates (LFPRs) in that region (Boserup, 1970). They find that differences in female labor supply are able to explain about 55% of the gender wage gap between the northern and southern states of India. Their paper highlights the importance of looking at LFPR as a determinant of gender wage gaps. However, this analysis would require a separate paper. Therefore, we take LFPRs as given, and conditional on participation analyze gender wage gaps.

Formal sector, urban labor markets, presumably more meritocratic, are not immune to gender wage differences either. Deshpande and Deshpande (1997) is an early overview study that documents summary statistics drawn from census and NSS reports about urban male and female employment, and moves to reporting statistics for the city of Mumbai on male and female employment, unemployment, occupational distribution, and wages. While the paper uses the term "discrimination", it demonstrates gender *differences* in these dimensions. Varkkey and Korde (2013) document gender pay gaps using paycheck data during 2006–13 for 21,552 respondents, of which 84% were males. These data are based on a *voluntary* internet survey conducted among formal sector workers, and hence, the sample is not representative. They find that the pay gap increased with skill level and position in the occupational hierarchy.[3] Duraisamy and Duraisamy (2005) use least squares as well as quantile regressions on NSS data for 1993–94 and estimate gender gaps in wage premia. They find that wage premia are lowest for primary education and highest for secondary education, and that wage premia, particularly for men, are higher in poorer states of India. They also find that expansion of primary education is associated with lowering of market rewards to education.

(b) Decomposing average gender wage gaps

The entire raw gender wage gap might not be due to discrimination in the labor market. The decomposition of wage/earnings gaps into the "explained" and the "unexplained" components has been widely used in order to tease out the effect of discrimination. In India, the BO decomposition method (Blinder, 1973; Oaxaca, 1973) has been used to decompose average wage and earnings gaps by caste (Banerjee & Knight, 1985; Deshpande & Sharma, 2016; Madheswaran & Attewell, 2007, among others) and religion (Bhaumik & Chakrabarty, 2009).

There are only a handful of studies that decompose average gender wage gaps in India; with only a couple of studies examining gender gaps at the all-India level, and changes therein over time.[4] Madheswaran and Khasnobis (2007) and Mukherjee and Majumder (2011) are national studies. The former uses the standard BO methodology, as well as its various refinements, and the latter examines "earning disparity" using the Theil Index, "occupation disparity" using the segregation index, "occupation choice" using a multinomial logit model, and estimates Mincerian wage equations, with decompositions for the latter two. Both these studies differ from our paper in terms of the time period, or in types of workers considered, but both point to an increase in the discriminatory component of the average gender wage gap, a finding similar to ours.

(c) Sticky floor or glass ceiling: what happens where?

We use Melly's refinement of the Machado–Mata (MM) methodology in order to decompose the gender wage gaps at each quantile of the earnings' distribution. This methodology, based on quantile regressions (Koenker & Bassett, 1978), has been used to analyze gender wage gaps in India in one earlier study (Agrawal, 2013). Studies

3 These findings are at variance with our findings of a sticky floor. This is perhaps because their sample is not representative and is restricted to internet users. Also their educational categories are not comparable to ours.

4 Studies focusing on a few states include Duraisamy and Duraisamy (1999) and Kingdon and Unni (2001).

such as Albrecht, Björklund, and Vroman (2003), Arulampalam, Booth, and Bryan (2007), De la Rica, Dolado, and Llorens (2008) show that in several developed European countries, women face a glass ceiling, i.e., the gender wage gap is higher at the higher quantiles, with a sharp acceleration at the upper tail of the distribution. However, developing countries such as China (Chi & Li, 2008), along with European countries such as Spain (Arulampalam *et al.*, 2007), are characterized by a "sticky floor". These terms are used to describe both the raw wage gaps, as well as the unexplained or discriminatory part of the gap in general discussions. Arulampalam *et al.* (2007) define a "glass ceiling" as existing if the 90th percentile wage gap is higher than the wage gap at all other parts of the wage distribution by at least two percentage points. Similarly, they define a "sticky floor" when the wage gap at the 10th percentile is higher than that at the 25th percentile by at least two percentage points. An alternate weaker definition would be to maintain the 2 percentage points criterion, but compare the 10th and the 50th percentile instead. These definitions have become fairly popular in the literature and are used in several papers as a rough rule to establish the presence of a sticky floor. Whereas Agrawal (2013) finds a glass ceiling overall, with urban women facing a sticky floor and rural women a glass ceiling, our results show that using both these definitions women in the RWS sector in India face a sticky floor, not a glass ceiling, and this result holds for all workers, as well as separately for rural and urban workers. The reason for this difference in results could be that we are focusing exclusively on RWS workers, (for reasons explained in the Section 1), whereas Agarwal presumably is focusing on all workers (the paper does not specify if he is using a subset or all workers for whom wage data are available). The majority of RWS workers are urban (65% in 2009–10) for whom Agarwal also finds a sticky floor. Additionally, both the data set and the time period of the Agarwal study are different from ours.

3. Methodology

(a) The Blinder–Oaxaca methodology

The Blinder–Oaxaca (BO) decomposition method decomposes the difference in the arithmetic mean of logarithm of wages between two groups, in our case, men and women.

The following semi-log regression equation is run for both groups separately

$$\ln(W_{si}) = \beta_{s0} + \sum_{k=1}^{K} X_{ski}\beta_{sk} + u_{si} \tag{1}$$

where s can be either "m" or "f", (male or female), i stands for individual, W for wage, X for the set of covariates (wage earning characteristics). There are K covariates such as age, education, and caste status and these are indexed by k. β represents the coefficients (returns to covariates). We assume that $E(u_{si}|X_i) = 0$. Given that the residuals from an OLS have zero arithmetic mean:

$$\overline{\ln(W_m)} = \widehat{\beta_{m0}} + \sum_{k=1}^{K} \overline{X_{mk}}\widehat{\beta_{mk}} \tag{2}$$

and, similarly for women:

$$\overline{\ln(W_w)} = \widehat{\beta_{w0}} + \sum_{k=1}^{K} \overline{X_{wk}}\widehat{\beta_{wk}} \tag{3}$$

Therefore,

$$\overline{\ln(W_m)} - \overline{\ln(W_w)} = \left[\widehat{\beta_{m0}} + \sum_{k=1}^{K} \overline{X_{mk}}\widehat{\beta_{mk}}\right] - \left[\widehat{\beta_{w0}} + \sum_{k=1}^{K} \overline{X_{wk}}\widehat{\beta_{wk}}\right] \tag{4}$$

To decompose this total difference, we add and subtract a counterfactual average wage. If we assume that the true or the non-discriminatory wage structure prevailing in the market is the one faced by men, and if women were to be paid according to this wage structure, then the average wage for a woman would be represented by,

$$CF_w = \left[\widehat{\beta_{m0}} + \sum_{k=1}^{K} \overline{X_{wk}}\widehat{\beta_{mk}}\right] \tag{5}$$

where CF stands for counter-factual. Adding and subtracting CF_w to Eqn. (4) above, we get,

$$\overline{\ln(W_m)} - \overline{\ln(W_w)} = \underbrace{[\widehat{\beta_{m0}} - \widehat{\beta_{w0}}] + \sum_{k=1}^{K} \overline{X_{wk}}(\widehat{\beta_{Mk}} - \widehat{\beta_{wk}})}_{\text{"D" Unexplained (Discrimination)}} + \underbrace{\sum_{k=1}^{K} (\overline{X_{mk}} - \overline{X_{wk}})\widehat{\beta_{mk}}}_{\text{"E" Explained (characteristics)}} \tag{6}$$

The first two terms are that part of the total differential which arise out of the differing returns of men and women to the labor market characteristics. This difference in coefficients can be thought of as the discrimination component, as it leads to a wage differential between the two groups even if both possess exactly the same vector of (average) covariates. The final term represents the difference in average logarithm of wages that is due to different average levels of covariates between men and women. This is the explained component of the average gender log wage gap.

Depending on the assumption about the non-discriminatory wage structure, we could have done the above decomposition differently. If the assumption is wage structure that will prevail in the absence of discrimination is the one faced by women, then the relevant average counterfactual wage would be CF_m:

$$CF_m = \left[\widehat{\beta_{w0}} + \sum_{k=1}^{K} \overline{X_{mk}}\widehat{\beta_{wk}}\right] \tag{7}$$

This is the wage paid to a person who possesses the characteristics of a representative male worker but is paid according to the wage structure that females face. Adding and subtracting this to Eqn. (4), we get the following alternative decomposition,

$$\overline{\ln(W_m)} - \overline{\ln(W_w)} = \underbrace{[\widehat{\beta_{m0}} - \widehat{\beta_{w0}}] + \sum_{k=1}^{K} \overline{X_{mk}}(\widehat{\beta_{mk}} - \widehat{\beta_{wk}})}_{\text{"D" Unexplained (Discrimination)}} + \underbrace{\sum_{k=1}^{K} (\overline{X_{mk}} - \overline{X_{wk}})\widehat{\beta_{wk}}}_{\text{"E" Explained (characteristics)}} \tag{8}$$

This is the familiar index number problem. The two examples of counterfactuals can be thought of as two extremes, one representing an upper limit and the other a lower limit of discrimination. Other assumptions of non-discriminatory wage structures can be thought of as weighted averages of the two sets of coefficients.[5]

[5] Cotton (1988) used sample proportions of each group as weights, that is, $\widehat{\beta_C} = \rho_M\widehat{\beta_M} + \rho_W\widehat{\beta_W}$, where ρ_M and ρ_W are sample proportions of men and women. The decomposition is done as follows:

$$\overline{\ln(W_m)} - \overline{\ln(W_w)} = \underbrace{[\widehat{\beta_{M0}} - \widehat{\beta_{C0}}] + \sum_{k=1}^{K} \overline{X_{MK}}(\widehat{\beta_{Mk}} - \widehat{\beta_{Ck}})}_{\text{Male Treatment Advantage}} + \underbrace{[\beta_{C0} - \widehat{\beta_{W0}}] + \sum_{k=1}^{K} \widehat{X_{WK}}(\widehat{\beta_{Ck}} - \widehat{\beta_{Wk}})}_{\text{Female Treatment Disadvantage}} + \underbrace{\sum_{k=1}^{K} (\overline{X_{MK}} - \overline{X_{WK}})\widehat{\beta_{Wk}}}_{\text{"E" Explained(characteristics)}}$$

We provide estimates using the two counterfactuals explained above, and a third set of estimates that uses coefficients from the pooled (men and women combined) OLS regression as the true wage structure.

(b) Quantile regression decomposition methods

Quantile Regression (QR) methods are a generalization of the B–O mean decomposition to decomposing at quantiles. There are several such methods and our focus is on the Machado and Mata (2005) (MM) methodology. We use Melly's refinement of the MM methodology (hereafter, MMM).

QRs assume that the conditional quantile of the dependent variable y is linear in covariates X. Therefore, the θ^{th} quantile of the conditional distribution is given by

$$Q_\theta(y_i|X_i) = X_i\beta_\theta, \quad \theta \in (0,1) \tag{9}$$

The estimate of β_θ solves the following minimization problem:

$$\sum_{i=1}^{n}\rho_\theta(y_i - X_i\beta_\theta) \tag{10}$$

where,

$$\rho_\theta(u) = \begin{cases} \theta * u, & u \geqslant 0 \\ (\theta - 1) * u, & u < 0 \end{cases} \tag{11}$$

Quantile regressions allow us to estimate the marginal effect of various wage-earning characteristics at each quantile.

The MM decomposition estimates the entire distribution using quantile regressions. The four steps of the MM procedure to generate a counterfactual log wage distribution are:

1) A random sample of size n is generated from a uniform distribution $U[0,1] : u_1, u_2 \ldots, u_n$.
2) For men and women separately, n QRs are estimated using the draw values from step 1) as the quantiles at which to estimate the QRs. Thus, we get $\{\hat{\beta}^M_{u_j}\}^n_{j=1}$ and $\{\hat{\beta}^W_{u_j}\}^n_{j=1}$, the n coefficient vectors for men and women, respectively.
3) Next a random sample with replacement of size n is taken from the covariate distribution of men and women separately. Let this be denoted by $\{\tilde{X}^M_j\}^n_{j=i}$ and $\{\tilde{X}^W_j\}^n_{j=i}$.
4) Finally, the counterfactual distributions are estimated as $\{Y^{cf}_j = \tilde{X}^M_j\hat{\beta}^W_{u_j}\}$ or $\{Y^{cf}_j = \tilde{X}^W_j\hat{\beta}^M_{u_j}\}$ for $j = 1, 2 \ldots, n$.

The first counterfactual distribution represents a distribution of log wages of men being paid according to the female wage structure, as it uses the covariates of men and returns of women. The second counterfactual represents the case where women retain their characteristics and get "paid like men".

Melly (2006)'s procedure is numerically equivalent to the MM procedure, but is computationally less intensive, since it does not rely on simulations to obtain the covariate vectors. Unlike the MM procedure that relies on a random draw of n vectors from the distribution of covariates, the MMM uses all observations on covariates and combines with each observation the n quantile regression coefficients to generate the unconditional (marginal) distribution of log wages. Thus, the conditional distribution is integrated over the entire range of covariates to obtain the unconditional distribution. Estimating the unconditional distribution this way has the advantage of using all the information contained in the regressors and this makes the MMM estimator more efficient than the MM estimator.

At the θ^{th} quantile, the difference between the estimated unconditional quantile of log wage for men, $\hat{Q}_m(\theta)$, and the estimated unconditional quantile of log wage for women, $\hat{Q}_w(\theta)$, can be decomposed as,

$$\hat{Q}_m(\theta) - \hat{Q}_w(\theta) = \underbrace{\left[\hat{Q}_m(\theta) - \hat{Q}_{cf}(\theta)\right]}_{\text{Effects of Coefficients}} + \underbrace{\left[\hat{Q}_{cf}(\theta) - \hat{Q}_w(\theta)\right]}_{\text{Effects of characteristics}} \tag{12}$$

where $\hat{Q}_{cf}(\theta)$ is the estimated counterfactual unconditional quantile of log wage for men created using the coefficients of women.

4. Data and descriptive statistics

We use data from the 55th and 66th rounds of NSS-EUS for the years 1999–2000 and 2009–10 respectively. The EUS provides wage information for both casual laborers (CL) and Regular Wage/Salaried (RWS) workers. NSS defines RWS workers as those who worked in others' farm or non-farm enterprises and received salary or wages on a regular basis (as opposed to the daily or periodic renewal of work contracts). We focus on RWS workers because for the most part, they are in formal sector jobs that are presumed to be meritocratic, as well as governed by regulations that do not sanction discrimination. It is therefore more interesting (and troubling) if we find evidence of labor market discrimination among RWS workers. Also, it would not be unreasonable to assume that if RWS workers exhibit gender gaps, then gaps among informal or casual workers are likely to be higher. Furthermore, the link between characteristics such as education and wages is likely to be tenuous for CL, given that CL are mainly employed in unskilled manual work. Thus, wage decompositions for RWS workers are likely to give a more accurate picture of discrimination.

Our sample consists of full-time RWS workers between the ages 15 and 59.[6] We calculate daily wage rates by dividing the total weekly earnings by the total days worked in that week.[7] Nominal wage rates are converted into real terms (1999–2000 prices) using separate state-level deflators for urban and rural areas.[8] Finally, we trim the sample at the two ends, removing the top and bottom 0.05% of the wage distribution in order to remove outliers and possible data entry errors. We are left with 34,131 observations for 1999–2000 and 33,676 observations for 2009–10.

(a) Labor force participation

Between 1999–2000 and 2009–10, LFPRs for both men and women have declined: from 86 to 83% for men, and from 33% to 28% for women.[9] The persistence of low female LFPRs by international standards[10] in the context of high growth is both a theoretical

[6] To be sure that we captured only RWS workers, we only considered those individuals who reported RWS to be their principal activity in the week preceding the survey.

[7] EUS allows an individual to report multiple jobs during a week. However, overwhelming majority of RWS workers (above 98% in both years) report being involved in only one activity. We restrict our analysis to these workers and calculate the wage rate using this single activity that they are involved in.

[8] For urban areas we use the Consumer Price Index for Industrial Workers (CPI-IW) and for rural areas we use the Consumer Price Index for Agricultural Labor (CPI-AL).

[9] We have tested for the statistical significance of all results in this section. We use a test of difference in proportions when comparing within year gender differences in shares, and an OLS wage equation with a gender dummy when looking at within year gender wage gaps. Additionally, we use a Difference-in-Differences specification (interaction of gender and year dummies) when examining whether the changes over the decade were significantly different for men and women.

[10] Globally, female LFPRs have remained stable over 1990–2010 at roughly 52%. This average conceals a great deal of regional heterogeneity: Female LFPRs vary between around 33% in North Africa, West and South Asia; and 66% in East Asia and sub-Saharan Africa. Global male LFPRs have declined over this period from 81% to 77%, reflecting an increase in educational enrollment rate among younger men (Chaudhary & Verick, 2014)

Table 1
Categorizing the labor force (% of labor force)

	1999–2000			2009–10		
	Males	Females	All persons	Males	Females	All persons
Casual labor	31.5	42.3	34.4	32.5	38.8	34.0
Regular Wage Salaried	18.1	9.3	15.7	18.7	12.7	17.3
Self employed	47.4	45.9	47.0	46.5	44.9	46.1
Unemployed	3.1	2.5	2.9	2.4	3.5	2.6
Total	100	100	100	100	100	100

and an empirical puzzle, the analysis of which is beyond the scope of this paper.

Table 1 gives the breakup of labor force into four mutually exclusive work categories. In both years, majority of women in the labor force are either casual laborers or are self-employed, with these two categories comprising about 84% of women in 2009–10. In both years, a larger share of women work as casual laborers compared to corresponding shares for men, and a smaller share work as RWS workers. The change over the decade shows that the RWS share among men and women has increased, from 18.1% to 18.7% for men), and to a larger extent, from 9.3% to 12.7% for women, resulting in a decline in the gender difference in RWS shares over the decade.

(b) Regular Wage Salaried (RWS) employment

RWS workers constitute about 17% of the labor force. Among all RWS workers, over the ten-year period, there has been a small, albeit statistically significant, increase in the proportion of women (from% 15.8 to 17.8%), and a corresponding decrease in the proportion of men (from 84.2% to 82.2%). However, men continue to get the overwhelming share of RWS jobs.

The gender wage gap among RWS workers is substantial in both years. The (raw/unconditional) gender wage gap at the mean is 55% in 1999–2000 and it is 49% in 2009–10.[11] This change over the decade is not statistically significant. In both years, the gap is substantially higher at the first decile compared to the median and the ninth decile, even though there is a significant decline in the gender wage gap at the median from 76% to 53%. At all points in the wage distribution, male wages are higher than female wages.

Figure 1 shows the gender wage gaps for both years at the mean and across percentiles. We see that in both years, the gaps are higher at lower end of the wage distribution and decline, across the distribution, revealing the "sticky floor". For most percentiles between the 15th to the median, gaps have declined over the decade, whereas they have mostly increased between the 70th to 80th percentiles. For 2009–10, the unconditional log wage gap at the 10th percentile is 0.72, whereas the gap at the 25th percentile is 0.52. This is a 20 percentage point difference, far greater than the 2 percentage point difference used in the literature to establish the sticky floor. The difference between log wage gaps at the 10th percentile and the 50th percentile is even greater (29 percentage points). For 1999–2000, the gender gap is the same for the 10th and the 25th percentile (0.69). However, the gap between the 10th and 50th percentile is 13 percentage points. Hence, even in 1999–2000, gender gaps were characterized by a sticky floor using the alternate weaker definition. Therefore, the sticky floor has become "stickier" for RWS women over this ten-year period.

(c) Gender differences in characteristics

There are several factors that might account for these gender wage gaps within RWS workers. Men and women could differ in terms of their observable characteristics such as age; urban or rural residence; educational attainment; occupation and industry of employment; type of job such as public sector *versus* private sector, temporary *versus* permanent, unionized *versus* non-unionised; their social groups such as caste and religion; and their region of residence (geographical location within the country). We have examined each of these factors separately[12]; here, some key factors are summarized.

In 2009–10, the average RWS worker was 35.6 years old. In both years, men are older than women by about a year. While age is used as a proxy for experience, we should note that women often drop out of jobs during childbearing years and resume after a few years, so they might have lower experience than men of the same age who would have been working continuously.

(i) Educational attainment

Table 2 shows that the proportion of illiterates and of "graduates and above" is higher among women than among men for both years. In 2009–10, 43% of female RWS workers had at least a graduate degree, compared to only 34% for males. Not only is the share of women in the highest educational category greater than that of men, it records a larger increase over the decade (16 percentage points for women) compared to men (11 percentage points for men). The decline in the share of illiterates is also greater for women (7.5 percentage points) compared to men (3.4 percentage points). Thus, over the decade, the educational attainment of women has improved relative to men.

Table 2 also shows that, for both years, gender wage gaps exist within each category of education. Similar to the sticky floor phenomenon, gender wage gaps are much higher at the lower end than at the higher end of the educational spectrum. Gender wage gaps did not change significantly over the decade for any of the education categories except for secondary and higher secondary education. For this category, the gap increased from 38 to 63% over the period.

(ii) Occupational and Industrial distribution

There are clear gender differences in occupational distribution in both years.[13] "Professionals and Associate Professionals" (representing the higher end of the earning spectrum) form the largest occupational category for women in both years, employing close to 45% of all RWS women. The share of women in this category is over 17 and 22 percentage points more than the corresponding share for men in 1999–2000 and 2009–10, respectively. In the category

[11] Gender wage gap at the mean is defined as the difference between the arithmetic means of logarithm of wages of men and women and is mathematically equivalent to $\log\left(\frac{GM_{men}}{GM_{women}}\right)$ where GM refers to the geometric mean for that group. Throughout the paper, the gender wage gap at the mean expressed in percentage refers to $\frac{GM_{men}-GM_{women}}{GM_{women}} * 100$.

[12] All the results are available with the authors upon request.

[13] Workers are divided into seven occupational categories that correspond roughly to the NCO 2004 one-digit occupational classification used in 2009–10. Two different occupation classification systems have been used for the 55th and 66th rounds of the NSS: these are NCO 1968 and NCO 2004, respectively. We created our own concordance to arrive at the seven broad occupational categories used in this paper.

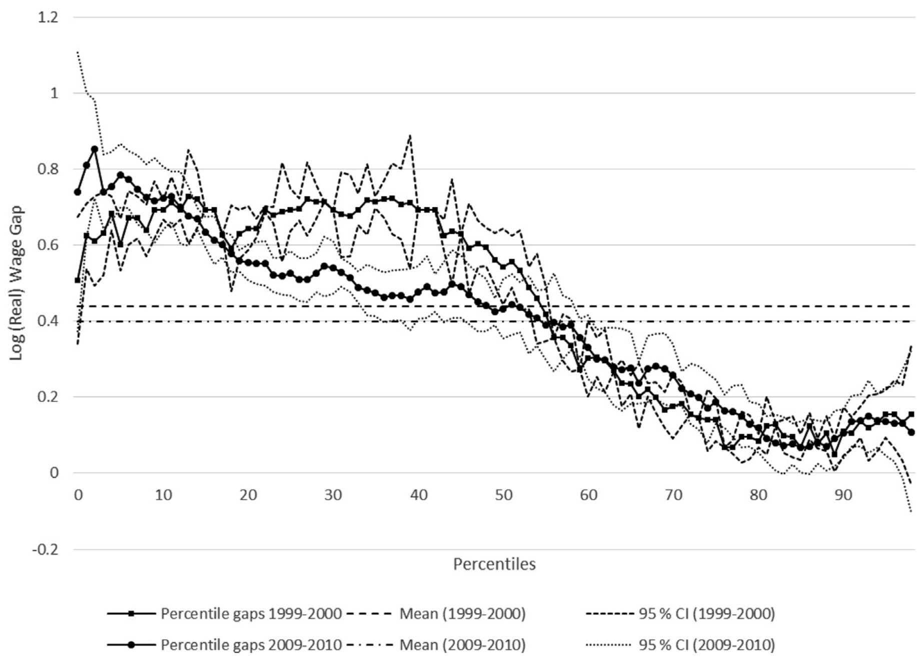

Figure1. Gender wage gaps across percentiles and at the mean (with Confidence Intervals, CI), 1999–2000 and 2009–10.

Table 2
Education shares and wages by gender

	1999–2000			2009–10		
	Male	Female	All persons	Male	Female	All persons
			Educational distribution of RWS workers (in %)			
Illiterates	9.4	22.5	11.5	6.1	14.9	7.6
Primary and below	17.3	13.7	16.7	14.0	12.0	13.6
Middle	17.5	9.6	16.3	16.2	10.6	15.2
Secondary, higher sec.	33.1	28.0	32.3	30.0	19.9	28.2
Graduate and above	22.7	26.3	23.3	33.8	42.6	35.3
Total	100	100	100	100	100	100
			Average wages (in 1999–2000 rupees per day)			
Illiterates	80.8	47.1	70.6	83.8	49.1	72.0
Primary and below	92.1	59.8	88.0	89.8	56.5	84.7
Middle	106.7	65.2	102.9	108.4	64.2	103.0
Secondary, higher sec.	160.3	140.4	157.7	163.0	116.6	157.3
Graduate and above	266.7	212.9	257.2	305.2	248.3	293.3
Overall	155.8	120.3	150.3	187.2	149.9	180.7
			Gender log wage gap (in % at the mean)			
			1999–2000			2009–10
Illiterates			76.4***			94.0***
Primary and below			62.0***			67.9***
Middle			84.2***			76.8***
Secondary, higher sec.			38.4***			63.4***
Graduate and above			33.5***			30.6***
Overall			55.1***			49.1***

† Indicates significance at 10%, * at 5%, ** at 1% and *** at 0.1%.

"Craftsmen and Machine Operators", the male proportion is 17 and 23 percentage points more than the corresponding female proportion in 1990–2000 and 2009–10, respectively. Gender differences in proportions across occupations range from less than 1 percentage point (e.g., clerks and skilled agriculture) to 23 percentage points.

There exists a gender wage gap in almost all categories of occupation.[14] At the lower end of the occupational spectrum, viz., Laborers and Unskilled Workers, wage differentials increased from 62% to 93%, while for Craftsmen and Machine Operators the gap decreased from 140% to 93% over the period. Examining the gender differences using a sevenfold division of industries, we find that for both years, the proportions of men are significantly different from women in all industries.

(iii) Public/private sector, union membership, and permanent/temporary jobs

Table 3 shows that the proportion of all RWS workers in the public sector has gone down over the decade from 37% to 34%. In both years, a higher share of RWS women are in public sector jobs compared to RWS men. Over the ten-year period, the share of private sector jobs among RWS men rose from about 64% in 1999–2000 to

[14] Except for "Administrators and Managers" in both years and for "Skilled Agriculture and Fishery workers", and "Clerks and Related workers" in 1999–2000.

Table 3
Shares and wages across employment types by gender

Public/private	1999–2000			2009–10		
	Male	Female	All persons	Male	Female	All persons
Public/private distribution of RWS workers						
Public sector	36.2	39.1	36.7	32.1	39.8	33.5
Private sector	63.8	60.9	63.3	67.9	60.2	66.5
Total	100	100	100	100	100	100
Average wages (in 1999–2000 rupees per day)						
Public sector	229.9	186.9	222.9	291.7	215.2	275.9
Private sector	120.4	86.2	115.4	141.4	111.1	136.7

Gender log wage gap (in % at the mean)	1999–2000	2009–10
Public sector	42.8***	68.5***
Private sector	68.2***	52.2***

Union/non-union	1999–2000			2009–10		
	Male	Female	All persons	Male	Female	All persons
Union distribution of regular salaried workers						
Non-union member	54.1	54.2	54.1	66.6	67.2	66.7
Union member	45.9	45.8	45.9	33.5	32.8	33.4
Total	100	100	100	100	100	100
Average wages (in 1999–2000 rupees per day)						
Non-union member	112.4	74.8	106.6	143.5	104.7	136.7
Union member	207.9	175.5	202.9	275.4	245.8	270.4

Gender log wage gap (in % at the mean)	1999–2000	2009–10
Non-union member	68.8***	61.5***
Union member	39.1***	23.4***

Temporary/permanent	1999–2000			2009–10		
	Male	Female	All persons	Male	Female	All persons
Permanent/temporary distribution of regular salaried workers						
Temporary	27.3	28.7	27.5	31.8	31.1	31.7
Permanent	72.8	71.3	72.5	68.2	68.9	68.3
Total	100	100	100	100	100	100
Average wages (in 1999–2000 rupees per day)						
Temporary	79.1	50.9	74.6	98.32	71.97	93.84
Permanent	184.7	148.8	179.2	228.72	185.58	221.16

Gender log wage gap (in % at the mean)	1999–2000	2009–10
Temporary	70.9***	54.7***
Permanent	46.3***	47.6***

†Indicates significance at 10%, * at 5%, ** at 1% and *** at 0.1%.

68% in 2009–10, whereas for women the change was minimal. In both years, within each sector, women are, on average, paid less than men. Notably, whereas the gender wage gap increased in the public sector (from 43% in 1999–2000 to 69 in 2009–10) it decreased in the private sector (from 68% in 1999–2000 to 52 in 2009–10).

Among RWS workers, the proportion of union members declined by 13 percentage points over the decade reflecting global trends. However, the share of unionized men and women is not different from each other, which is an interesting feature of the Indian labor market. In both years, average wages of women within both members and non-members are significantly less than that for men. The gender wage gap declined significantly for union members over the decade.

A similar analysis of permanent or temporary work status reveals that overall, the share of permanent workers has gone down over the decade from roughly 73% to 68%. The share of permanent workers is no different between men and women. Women are paid less than men within both the permanent and temporary categories. It is also interesting to note that the gender wage gaps declined significantly among temporary workers, but not among permanent workers.

(iv) Caste and religion

Indian society is marked by multiple cleavages, caste being another critical axis of differentiation and disadvantage. The overlap of gender and caste introduces a new complex dimension in overall disparities, in that restrictions on women's work outside the home, and on their public visibility have historically been greater among higher ranked castes.

While a detailed assessment of the gender-caste overlap is outside the scope of this paper,[15] we discuss some salient factors in the

[15] See Deshpande (2007, 2011) for a discussion of the gender-caste overlap.

Table 4
Caste shares and wages by gender

	1999–2000			2009–10		
	Male	Female	All persons	Male	Female	All persons
			Caste distribution of RWS workers (in %)			
Scheduled tribe	5.2	7.2	5.5	4.8	5.0	4.8
Scheduled Caste	14.8	15.4	14.9	16.3	19.4	16.9
Other Backward Classes	29.4	29.5	29.4	35.7	34.9	35.5
Upper Caste	50.7	47.8	50.3	43.2	40.7	42.8
Total	100	100	100	100	100	100
			Average wages (in 1999–2000 rupees per day)			
Scheduled Tribe	155.5	112.9	146.7	172.5	128.3	164.4
Scheduled Caste	131.7	89.9	125.0	151.0	90.6	138.9
Other Backward Classes	128.8	87.3	122.3	166.7	124.8	159.6
Upper Caste	178.4	151.5	174.4	219.4	202.3	216.6
			Gender log wage gap (in % at the mean)			
			1999–2000			2009–10
Scheduled Tribe			54.4***			61.8***
Scheduled Caste			65.5***			86.5***
Other Backward Classes			78.5***			50.7***
Upper Caste			38.0***			28.1***

† Indicates significance at 10%, * at 5%, ** at 1% and *** at 0.1%.

context of RWS employees. Data on caste are available by broad administrative categories: Scheduled Castes (SC), Scheduled Tribes (ST), and Other Backward Classes (OBC)—groups of castes, tribes, and communities identified as beneficiaries of affirmative action due to accumulated disadvantage, and in the case of SCs and STs added stigmatization on account of their caste/tribe status. Those who are not eligible form a heterogeneous residual category of "Others" (everyone else), a rough proxy for Upper Castes (UC).[16]

From Table 4 we note that the proportion of UC RWS workers has decreased from 50.3 to 42.8. This decrease is mirrored in the rise in the proportion of OBC workers from 29.4 to 35.3 and in SC workers from 14.9% to 16.9%.

There are gender wage gaps within all caste categories. There is a significant decrease in the gender wage gap for OBCs over the decade. For other caste categories, gender wage gaps did not change significantly over time. SC women are likely to be concentrated at the lower end of the wage distribution and could possibly account for a large part of the sticky floor.

Hindus form the largest proportion of RWS (83% in both years), reflecting their share in the population. In both years, the share of Muslims among RWS men is greater than their share among RWS women (in 2009–10, for men 10.2% and for women 5.6), while the opposite is true for Christians (3.0% for men and 6.7% for women). Gender wage gaps for Hindus, Muslims, and Christians are significant for both years.

5. Results

In this section, we first present the estimates for the gender wage gap at the mean (using OLS) and at several quantiles (using quantile regressions), conditioning for observable characteristics. Gender wage gap estimates based on two different regression specifications, namely partial and full, are presented. In the partial specification, log wages are regressed on only exogenous variables, viz., age, age squared, caste dummies, married, education dummies, urban residence, and regions; while in the full specification, additional controls for public sector, union membership, permanent job, occupation, and industry are also included.

(a) OLS results

Table 5 shows the OLS results for the pooled sample, and separately for men and women. The regression on the pooled sample includes a male dummy which is the main variable of interest. It captures the gender wage gap conditional on observable characteristics while assuming that the returns to these characteristics are the same for men and women. The top panel of Table 5 shows that, in both years, gender wage gaps exist even after accounting for differences in characteristics. For the partial specifications, in 1999–2000 the gender wage gap at the mean is 39%, and in 2009–10 it is 46%. To reiterate, the gender wage gaps in percentages has been calculated from the exact transformation as given by $(e^{\hat{\beta}} - 1) * 100$. This corresponds to the percentage difference in the geometric means of wages of men and women, as explicitly mentioned in Footnote 11.

Interestingly, when we move from the partial to the full specification, the gender gaps *increase* to 45% and 54% in 1999–2000 and 2009–10, respectively. This suggests that RWS women have better job characteristics compared to men in terms of the types of jobs, and the occupation and industry of employment.

Separate regressions for men and women reveal that the labor market rewards the same characteristics very differently for men and women. The full specification for 2009–10 shows that the coefficients of all the education variables are larger for women than for men, indicating that being educated has higher returns for women than men. Also, union membership has a stronger positive effect on female wages than male wages.

(b) Estimates from quantile regressions

Table 6 presents the gender wage gaps and returns to characteristics at the first, third, fifth (median), seventh, and ninth deciles for the full specification. The first panel using the pooled sample shows that gender wage gaps exists at all quantiles, even after conditioning for observable characteristics. Notably, moving from lower to higher quantiles, the gender wage gaps decrease: 87.8% at the first decile, which decreases to 40.4% at the ninth decile.[17]

[16] The "Others" group includes, but is not confined to, the Hindu upper-castes; however, it can be taken as a rough proxy for the latter. NSS data do not allow us to isolate Hindu upper castes. Note that this four-way division understates the gaps between the Hindu upper castes and the most marginalized SCs and STs.

[17] Separate results for rural and urban workers, which show the same pattern of declining gaps moving from lower to higher quantiles, are available from the authors upon request.

Table 5
OLS regressions, partial and full specifications, 1999–2000 and 2009–10[a]

	Partial				Full			
	1999–2000		2009–10		1999–2000		2009–10	
	Coeff.	*t*-ratio	Coeff.	*t*-ratio	Coeff.	*t*-ratio	Coeff.	*t*-ratio
	Pooled (men and women) sample							
Male	0.33	17.02	0.38	17.07	0.37	19.20	0.43	18.51
Age	0.06	14.36	0.03	5.76	0.04	9.03	0.02	4.65
Age squared	−0.04	−7.87	−0.01	−0.87	−0.03	−5.44	−0.01	−2.09
Married	0.16	8.55	0.13	5.72	0.07	3.97	0.08	3.74
Urban	0.17	10.93	0.21	10.45	0.18	11.56	0.25	13.59
ST	0.11	3.59	−0.02	−0.63	0.02	0.52	−0.08	−2.53
SC	−0.01	−0.39	−0.10	−4.62	−0.08	−4.02	−0.14	−7.01
OBC	−0.07	−5.23	−0.11	−5.61	−0.08	−6.50	−0.11	−5.89
Primary and below	0.22	9.75	0.20	6.67	0.10	4.22	0.10	3.28
Middle	0.38	18.02	0.36	12.05	0.20	8.98	0.20	7.04
Secondary, higher sec.	0.72	35.95	0.67	23.74	0.39	16.80	0.37	12.87
Graduate and above	1.15	47.61	1.30	42.12	0.68	24.54	0.73	17.61
Public	No		No		0.25	14.20	0.31	13.35
Union member	No		No		0.28	15.64	0.23	13.70
Permanent	No		No		0.26	16.70	0.25	15.23
Regions	Yes		Yes		Yes		Yes	
Occupation	No		No		Yes		Yes	
Industry	No		No		Yes		Yes	
R squared	0.48		0.46		0.59		0.56	
Observations	34,102		33,658		28,538		31,274	
	Male sample							
Age	0.06	13.59	0.03	6.09	0.04	8.43	0.03	5.30
Age squared	−0.05	−8.10	−0.01	−1.59	−0.03	−5.52	−0.02	−2.95
Married	0.16	7.10	0.12	4.48	0.09	4.21	0.08	3.09
Urban	0.16	9.77	0.18	8.39	0.15	9.55	0.21	10.78
ST	0.09	2.88	−0.03	−0.75	−0.01	−0.38	−0.09	−2.66
SC	−0.03	−1.42	−0.09	−3.87	−0.09	−4.36	−0.15	−7.23
OBC	−0.06	−4.51	−0.11	−5.15	−0.08	−5.87	−0.11	−5.41
Primary and below	0.16	7.21	0.09	3.03	0.03	1.25	0.01	0.39
Middle	0.32	14.42	0.25	8.22	0.14	5.82	0.12	4.02
Secondary, higher sec.	0.63	30.10	0.54	18.76	0.31	12.92	0.28	9.34
Graduate and above	1.05	37.60	1.12	33.39	0.57	18.54	0.56	13.32
Public	No		No		0.24	13.04	0.33	13.36
Union member	No		No		0.25	13.22	0.19	10.92
Permanent	No		No		0.22	13.81	0.24	13.57
Regions	Yes		Yes		Yes		Yes	
Occupation	No		No		Yes		Yes	
Industry	No		No		Yes		Yes	
R squared	0.47		0.44		0.58		0.55	
Observations	28,462		27,668		23,845		25,724	
	Female sample							
Age	0.05	4.49	0.03	2.62	0.02	1.65	0.02	1.94
Age squared	−0.02	−1.66	−0.01	−0.42	0.00	0.15	−0.01	−0.75
Married	0.11	3.04	0.08	2.01	0.03	0.96	0.03	0.83
Urban	0.21	5.04	0.33	8.01	0.26	6.26	0.37	9.16
ST	0.23	2.60	−0.03	−0.40	0.17	2.05	−0.09	−1.11
SC	0.10	2.18	−0.11	−1.93	0.01	0.2	−0.11	−2.08
OBC	−0.11	−2.80	−0.11	−2.47	−0.11	−2.53	−0.13	−2.93
Primary and below	0.30	4.58	0.31	4.65	0.23	3.5	0.19	2.82
Middle	0.43	7.33	0.49	6.70	0.30	4.26	0.31	4.49
Secondary, higher sec.	1.00	20.78	0.96	14.60	0.76	9.53	0.67	7.86
Graduate and above	1.45	34.06	1.71	30.09	1.11	13.59	1.33	11.75
Public	No		No		0.30	6.59	0.28	5.68
Union member	No		No		0.40	8.94	0.36	8.56
Permanent	No		No		0.40	9.33	0.29	6.97
Regions	Yes		Yes		Yes		Yes	
Occupation	No		No		Yes		Yes	
Industry	No		No		Yes		Yes	
R squared	0.46		0.49		0.6		0.59	
Observations	5,640		5,990		4,693		5,550	

[a] An intercept is included in all specifications. Base categories are: Illiterates for education, Others for caste.

We find that the gaps at the upper deciles (seventh and ninth) increase as we move from the partial to the full specification. This suggests that RWS women at the higher ends of the conditional distribution are in better jobs in terms of the type of job, occupation, and industry. It could be argued that a study of career advance is needed to fully understand sticky floor (or glass ceiling), and since occupation could account for career advance, controlling for occupation could eliminate a significant portion of the sticky floor effect. We should note that both with and without controls for occupation, we find a sticky floor.[18] Similarly, RWS workers in the

[18] The estimates without controls for job characteristics are available with the authors upon request.

Table 6
Quantile regressions, full specification, 2009–10[a]

	1st Decile		3rd Decile		Median		7th Decile		9th Decile	
	Coeff.	*t*-ratio	Coeff.	*t*-ratio[1]	Coeff.	*t*-ratio[1]	Coeff.	*t*-ratio	Coeff.	*t*-ratio
Pooled sample (*N* = 31,274)										
Male	0.63	28.18	0.49	35.07	0.39	25.98	0.32	19.66	0.34	15.22
Age	0.03	4.75	0.02	5.84	0.02	6.14	0.02	5.62	0.02	4.19
Age squared	−0.03	−3.74	−0.01	−2.67	−0.01	−2.49	−0.01	−1.75	−0.01	−1.33
Married	0.17	5.88	0.12	8.84	0.05	3.59	0.03	1.89	−0.01	−0.39
Urban	0.28	11.29	0.24	20.96	0.21	18.33	0.19	15.79	0.19	12.12
ST	−0.10	−2.15	−0.10	−4.36	−0.08	−3.10	−0.09	−3.53	−0.11	−3.44
SC	−0.13	−4.94	−0.11	−8.12	−0.15	−9.96	−0.16	−10.14	−0.13	−6.29
OBC	−0.11	−4.49	−0.08	−6.83	−0.10	−7.46	−0.10	−7.47	−0.12	−6.14
Primary and below	0.12	3.18	0.07	3.01	0.10	3.98	0.09	3.73	0.07	2.22
Middle	0.21	5.44	0.19	8.86	0.18	7.50	0.21	8.51	0.19	5.88
Secondary, higher sec.	0.35	9.50	0.34	16.48	0.33	14.58	0.37	15.39	0.38	12.40
Graduate and above	0.58	10.64	0.66	27.21	0.67	26.17	0.73	26.87	0.79	22.61
Public	0.30	10.48	0.37	25.17	0.40	26.46	0.33	20.40	0.24	9.23
Union member	0.28	12.30	0.28	23.82	0.23	18.67	0.17	12.82	0.13	6.36
Permanent	0.19	8.39	0.19	16.11	0.23	18.24	0.28	21.17	0.31	18.24
Regions	Yes		Yes		Yes		Yes		Yes	
Occupation	Yes		Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes		Yes	
Male sample (N = 25,724)										
Age	0.04	6.35	0.03	5.60	0.03	6.53	0.02	6.39	0.02	3.81
Age squared	−0.05	−5.53	−0.02	−3.21	−0.02	−3.41	−0.01	−2.30	−0.01	−1.22
Married	0.17	5.31	0.11	5.62	0.04	2.20	0.03	1.95	0.03	1.27
Urban	0.24	9.64	0.18	12.94	0.18	13.89	0.17	15.30	0.17	9.96
ST	−0.09	−2.03	−0.09	−3.16	−0.10	−3.66	−0.10	−3.90	−0.16	−5.28
SC	−0.13	−5.22	−0.14	−8.32	−0.15	−8.85	−0.16	−10.66	−0.15	−6.44
OBC	−0.10	−4.38	−0.10	−6.70	−0.09	−6.59	−0.10	−7.16	−0.10	−5.00
Primary and below	0.05	1.24	0.00	0.17	0.03	1.06	0.00	0.06	0.02	0.60
Middle	0.14	3.95	0.12	4.38	0.11	3.83	0.12	5.08	0.14	3.75
Secondary, higher sec.	0.27	7.48	0.26	10.08	0.27	10.01	0.29	12.18	0.32	9.22
Graduate and above	0.42	7.68	0.51	16.51	0.56	18.44	0.59	22.54	0.68	18.12
Public	0.37	12.62	0.43	23.21	0.41	23.46	0.33	20.60	0.25	9.22
Union member	0.27	12.42	0.24	16.36	0.19	13.90	0.14	10.64	0.12	5.71
Permanent	0.18	8.02	0.20	13.35	0.22	15.62	0.26	21.00	0.29	16.17
Regions	Yes		Yes		Yes		Yes		Yes	
Occupation	Yes		Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes		Yes	
Female sample (*N* = 5,550)[b]										
Age	0.01	2.18	0.03	.	0.01	.	0.03	8.17	0.01	10.33
Age squared	0.00	−0.04	−0.02	.	0.00	.	−0.02	−4.90	0.00	−1.00
Married	0.09	4.43	0.10	.	0.03	.	−0.03	−2.68	−0.09	−19.71
Urban	0.36	14.51	0.37	.	0.40	.	0.33	25.53	0.29	60.43
ST	−0.25	−4.65	−0.07	.	−0.04	.	−0.10	−4.37	−0.02	−3.08
SC	−0.18	−5.09	−0.08	.	−0.08	.	−0.12	−7.52	−0.17	−27.81
OBC	−0.18	−7.81	−0.06	.	−0.06	.	−0.12	−9.65	−0.16	−28.72
Primary and below	0.28	7.11	0.19	.	0.12	.	0.18	8.53	0.23	28.34
Middle	0.40	9.98	0.32	.	0.31	.	0.28	11.80	0.30	33.45
Secondary, higher sec.	0.59	12.71	0.75	.	0.62	.	0.53	21.58	0.56	51.39
Graduate and above	1.34	27.62	1.46	.	1.34	.	1.05	36.14	1.04	66.55
Public	0.37	12.15	0.31	.	0.32	.	0.31	22.59	0.18	28.12
Union member	0.41	15.41	0.42	.	0.43	.	0.34	26.82	0.16	29.83
Permanent	0.21	8.63	0.26	.	0.22	.	0.36	29.14	0.39	77.67
Regions	Yes		Yes		Yes		Yes		Yes	
Occupation	Yes		Yes		Yes		Yes		Yes	
Industry	Yes		Yes		Yes		Yes		Yes	

[a] An intercept is included in all specifications. Base categories are: Illiterates for education, Others for caste.
[b] For the only women sample at the 3rd decile and the median, the standard errors are very small and consequently the *t*-ratios are very large. We prefer not to present these *t*-ratios, and not to interpret the statistical significance of these coefficients.

NSS data would include all types of workers including domestic workers who work for households on a regular salary. The differences in jobs by gender are very sharp at the bottom of the distribution and may be captured as gender differentials in incomes. However, since we control for occupation, and still find a sticky floor, we can conclusively assert the presence of a sticky floor.

Finally, separate regressions for men and women reveal that, relative to being illiterate, the returns to the highest category of education, i.e., graduate and above seem larger at the first and second deciles compared to the seventh and ninth. For women, we notice that the return to being married is positive and significant at the bottom of the distribution, but is negative and significant for the top three deciles. For men, the return is positive and significant at all deciles, and declines at higher deciles.

(c) Decomposition results

(i) Blinder–Oaxaca decomposition

We decompose the gender wage gap at the mean using three counterfactual wage structures—the male wage structure, the

Table 7
Blinder–Oaxaca decompositions using full specification[a]

	1999–2000			2009–10		
	Alternate counterfactuals					
	Male	Female	Pooled	Male	Female	Pooled
Gender wage gap at the mean (in Logs)[b]	0.42	0.42	0.42	0.39	0.39	0.39
of which Explained	0.03	0.09	0.05	−0.07	0.04	−0.04
of which Unexplained	0.39	0.33	0.37	0.46	0.34	0.43
Percent Unexplained (Discriminatory)	92.3	77.8	88.2	119.1	88.5	111.1
Geometric mean (INR per day)			1999–2000			2009–10
Male Wage			118.3			131.0
Female Wage			77.4			88.9

[a] 28,538 observations in 1999–2000 (23,845 men and 4,693 women) and 31,274 observations in 2009–10 (25,724 men and 5,550 women).
[b] This refers to [AM of {Log(Male Wages)} – AM of {Log(Female Wages)}], where AM refers to Arithmetic Mean.

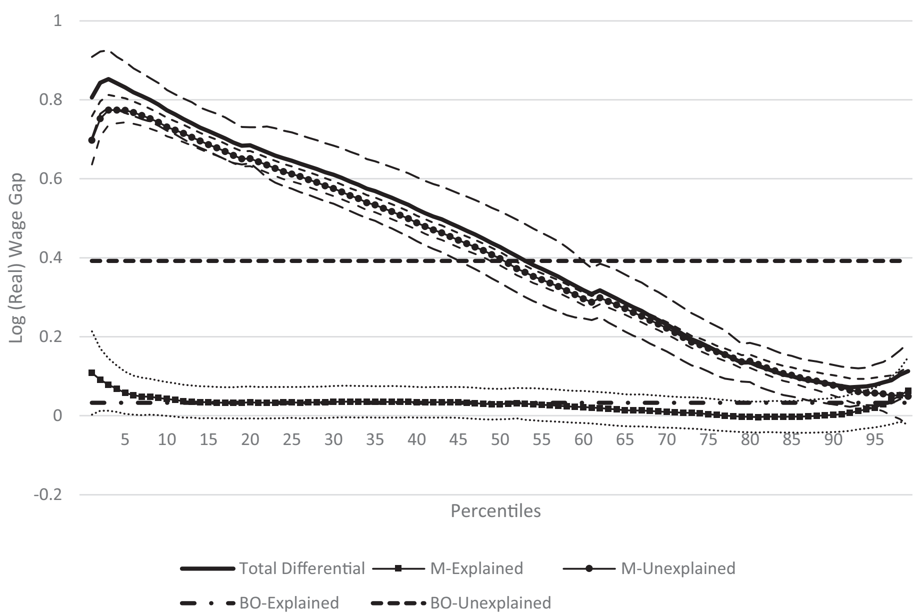

Figure 2. MMM decomposition using male wage structure, 1999–2000.

female wage structure, and the pooled wage structure. Table 7 presents the BO decomposition results for the two years using the full specification.

In both years, the overwhelming part of the male–female wage gap at the mean is unexplained. In 1999–2000, using the male, female, and pooled wage structures as the counterfactuals, 92, 78, and 88% of the wage gap respectively, was unexplained. The corresponding shares for 2009–10 are 119%, 89%, and 111%, respectively, indicating an increase in the unexplained component, suggesting that wage discrimination against women increased over this period. Interestingly, in 2009–10, using the male and the pooled wage structures as counterfactuals, the unexplained part of the wage gap is larger than the total wage gap itself (it is greater than 100%). This implies that if the labor market rate of compensation was the same across gender, women would have earned, on average, a higher wage than men given their superior characteristics. Compared to 2009–10, the explained component in 1999–2000 is smaller (for all three counterfactuals), indicating that over the decade the average characteristics of women in RWS employment improved relative to men.

(ii) MMM decomposition

Figures 2 and 3 and Table 8 present the overall gender wage gap, and its decomposition into the explained and the unexplained components for each percentile for the two years.[19] Similar to the BO decomposition at the mean, we note that the overwhelming part of the overall gender wage gap across most percentiles is unexplained or discriminatory (in both figures, the unexplained component closely tracks the overall wage gap).

Figure 2 shows that in 1999–2000, beyond the first decile, the explained component is insignificant throughout, while both the overall gender wage gap and the unexplained component are significant throughout.[20] Thus, in 1999–2000, if women were "paid like men", i.e., if they faced the same labor market returns to characteristics as men did, we would not see a wage gap between men and women beyond the first decile. Figure 3 shows that in 2009–10, the overall gender wage gap and the unexplained component remain significant over the entire distribution. However, unlike 1999–2000, the explained component is negative and significant beyond the third decile. This means that beyond the third decile, if women in RWS were "paid like men", they would have earned a higher wage than men due to better characteristics than the men.

Both figures also show that the overall gender wage gap as well as the unexplained component get smaller as we move from lower

[19] We also present the 95% confidence intervals (dashed lines) for each of these components based on bootstrapped standard errors.
[20] The unexplained component is insignificant only for the top two percentiles.

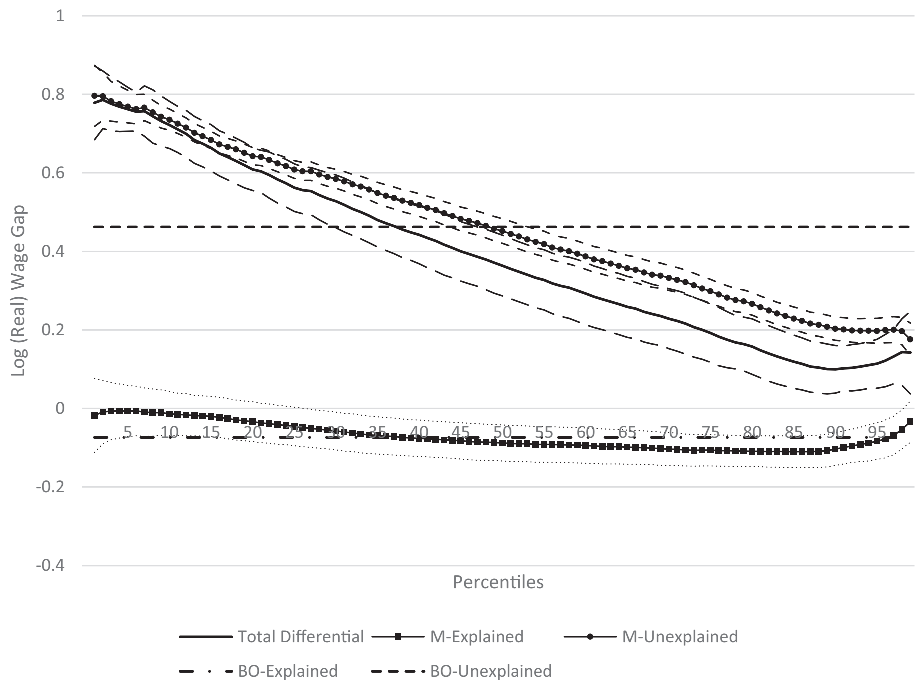

Figure 3. MMM decomposition using male wage structure, 2009–10.

Table 8
MMM decompositions using full specification (using male wage structure)

Decile	Gender wage gaps		
	Total	Explained	Unexplained
	1999–2000		
1	0.77 (0.03)	0.04 (0.02)	0.73 (0.01)
2	0.68 (0.02)	0.03 (0.02)	0.65 (0.01)
3	0.61 (0.04)	0.04 (0.02)	0.58 (0.01)
4	0.52 (0.04)	0.03 (0.02)	0.49 (0.01)
5	0.43 (0.05)	0.03 (0.02)	0.40 (0.01)
6	0.32 (0.04)	0.02 (0.02)	0.30 (0.01)
7	0.23 (0.04)	0.01 (0.02)	0.22 (0.01)
8	0.13 (0.03)	0.00 (0.02)	0.14 (0.01)
9	0.08 (0.03)	0.00 (0.02)	0.08 (0.01)
	2009–10		
1	0.72 (0.03)	−0.01 (0.03)	0.74 (0.01)
2	0.61 (0.03)	−0.03 (0.03)	0.64 (0.01)
3	0.53 (0.03)	−0.06 (0.02)	0.58 (0.01)
4	0.44 (0.04)	−0.08 (0.02)	0.52 (0.01)
5	0.36 (0.04)	−0.09 (0.02)	0.45 (0.02)
6	0.29 (0.04)	−0.09 (0.02)	0.39 (0.02)
7	0.23 (0.04)	−0.10 (0.02)	0.33 (0.02)
8	0.16 (0.04)	−0.11 (0.02)	0.27 (0.01)
9	0.10 (0.03)	−0.10 (0.02)	0.20 (0.02)

to higher percentiles. Thus, the discriminatory component of the gender wage gap also follows a sticky floor, revealing that women at the lower end of the distribution face greater discrimination. In both figures, juxtaposing the MMM decomposition on to the BO decomposition, we see that the unexplained part of the BO decomposition cuts the downward sloping curve for the unexplained part of the MMM decomposition roughly at the middle.

6. Discussion

We focus on the most recent decade, as this has been a period of rapid growth, new job openings, greater integration with the global economy, and increasing domestic privatization in India. While this paper is not a causal analysis of these changes on gender wage gaps and gender discrimination, it raises questions about the likely association between these structural changes and wage disparities, and more broadly about discrimination. Seguino (2000), in a cross-country study, finds that gender inequality, which lowers women's wages relative to men's, is actually a stimulus to growth in export oriented economies. This runs counter to the conventional wisdom that greater inequality (based on household income as a unit of measurement, obliterating gender gaps) is inimical to growth because it fuels social conflict. Seguino suggests that inequality is "less likely to produce social conflict if the burden is borne by women, a group traditionally socialized to accept gender inequality as a socially acceptable outcome" (p. 1212).

In India, we note that high growth has not been accompanied by an increase in female LFPRs. Also, in 2009–10, only about 10% of women in the labor force are in RWS jobs (as opposed to 16% for men), and the overwhelming share of RWS jobs are held by men (83%). Equally, if not more, worrying is the fact that women face adverse returns to their characteristics. In 2009–10, throughout the wage distribution, although women have better characteristics than men, they earn less than men due to labor market discrimination. Moreover, at the lower end of the wage distribution, for the bottom 10% where women face higher discrimination, the wage gaps have increased (Figure 1).

(a) The sticky floor

A major contribution of our paper has been to highlight the sticky floor phenomenon in the gender wage gaps picture for India. Recent studies on China (Chi & Li, 2008), Thailand (Fang & Sakellariou, 2011), Vietnam (Pham & Reilly, 2007) and the Philippines (Sakellariou, 2004) find a sticky floor effect for all these countries as well. This is in contrast to the glass ceiling that is observed in several developed countries.

Our study finds that the magnitudes of log wage gaps, at the mean and across quantiles, are much larger for India as compared to European nations. Consider the average wage gaps for the 24 countries examined in Christofides, Polycarpou, and Vrachimis

(2010). Only three of those European nations[21] had average gender log wage gaps greater than those found in India. Among the 11 countries studied in Arulampalam *et al.* (2007), the largest average gender log wage gap was found in Britain (0.25) and the lowest in Italy (0.063). Our study reveals an average log wage gap of about 0.4.

The decline in gender wage gaps as one moves from the bottom end to the top of the wage distribution is also quite drastic in the Indian case. If we look at the gender gaps due to the unexplained/discrimination component alone in the MMM results, again we find a very steep sticky floor that more than satisfies the Arulampalam *et al.* (2007) criteria. Thus, the sticky floor effect in India is particularly strong when compared to European countries that find a similar effect, such as Ireland, Italy, and Spain.

One issue that can be raised is whether a static analysis can capture a process that happens over time. To illustrate with the example of a glass ceiling: the definition of glass ceiling used in the labor economics literature is static, but it is, in fact, the result of dynamic processes. When women are less likely to be promoted, and if promoted likely to receive a smaller increase in income; and when the gender wage gap both grows and accelerates as one moves up the hierarchical order, the implications of these processes for the wage distribution is essentially what we examine: that is, are gender wage gaps higher at higher quantiles of the wage distribution? Having said this, it is true that we test this for two different cross-sections, which is the best we can do without panel data on individual men and women to track their career and the associated wage growth.

Another concern with using cross-sectional data is that it conflates experience and cohort effects. However, NSS data do not have specific information on work experience and the best we can do is control for age, which captures both experience and cohort effects. To the extent that older workers faced greater gender gaps and more experienced workers are concentrated at the top of the wage distribution, this should imply higher wage gaps for high-wage earners or a glass ceiling, which is contrary to what we have found. In that sense, the finding of the sticky floor is even more surprising.

A related point of whether cohort effects are behind the sticky floor can be addressed. We have tried to see whether the sticky floor can be explained by the following hypothetical situation, namely, younger age groups face higher wage gaps than older ones and since they tend to be found at the bottom of the wage distribution (because of lower experience), this contributes to the sticky floor. We find that this is not the case.

(b) Possible reasons for the sticky floor

One explanation for the sticky floor might be statistical discrimination by employers.[22] In India, social norms place the burden of household responsibilities disproportionately on women. Because of this, men are perceived by employers to be more reliable vis-à-vis women. Also, given the higher probability of dropping out of the labor market (for childbearing and rearing), employers discriminate against women when they enter the labor market because they expect future career interruptions. As women move up the occupation structure and gain job experience, employers become aware of their reliability and may perhaps discriminate less.

Another reason for the sticky floor could be that the nature of jobs are very different at the two ends of the distribution. Women working at the upper end are more likely to be the urban-educated elite working in managerial or other professional positions. These high-wage earning women are more likely to be aware of their rights and might be in a better position to take action against perceived discrimination. According to Arulampalam *et al.* (2007), "only the more articulate and better educated are willing to take legal action against breaches of the law" (p. 176). Employers would be aware of these possibilities themselves and hence, may not be able to discriminate a great deal between similarly qualified men and women at the upper end of the wage distribution. Moreover, the payment mechanism in jobs at the higher end would be far more structured and rigidly defined. Whether in the public sector or the private sector, most high-paying jobs will have written contracts with predefined clauses for basic increases in salaries, year on year, thus making it harder to discriminate across genders.

Contrast this to a situation where an employer is paying a regular wage to a woman with no education working in an elementary occupation, a typical example of a worker at the bottom of the wage distribution in the Indian context. It is easier for the employer to discriminate in this case, as these jobs might be outside the jurisdiction of labor laws. Article 39 of the Indian constitution envisaged equal pay for equal work for both men and women. To this end legislations such as the Equal Remunerations Act (1976) were enacted. To the extent minimum wage laws are not strictly adhered to, there would be larger gender wage gaps at the bottom of the distribution. Women at the bottom may also have less bargaining power compared to men due to family commitments or social custom and are more likely to be subject to the firms' market power.

Job segregation is also a known contributor to wider gaps at the bottom as men and women only enter into exclusively "male" and "female" jobs. Low-skilled jobs for women may pay less than other jobs that require intense physical labor, which are predominantly male jobs. Our model specifications control for broad industry and occupation groups; however, *within* certain low-paying broad industrial categories men and women could be doing different kinds of jobs and that could be picked up as the discrimination component.

7. Concluding comments

Using data from two rounds of the EUS of NSS for 1999–2000 and 2009–10, and examining gender gaps among workers in Regular Wage/Salaried jobs, this paper shows that the involvement of women in RWS work has increased over the decade, but remains low—of all women in the labor force, only 13% are in RWS jobs in 2009–10 compared to 19% for men. Over the decade, educational qualifications of women in RWS jobs have increased such that in 2009–10, greater proportions of RWS women have higher education than men, but this has not been accompanied by a decline in the average wage gap. The overwhelming part of the wage gap cannot be explained by characteristics, or is possibly discriminatory. Also, the unexplained or discriminatory part of the average wage gap has increased over the decade. In particular, given the improvement in female wage-earning characteristics over the decade, if women were "paid like men", women would have earned a higher average wage than men. Going beyond averages, decomposing the wage gaps along the entire wage distribution, we find that gaps are higher at the lower end of the distribution than the upper end, i.e., women in India face a "sticky floor", not a glass ceiling. Not only are the gaps higher at the lower end, the discriminatory part of the gap is also higher for workers at the lower end of the wage distribution. Over the decade, the gap has declined in the lower middle of the wage distribution.

This picture presents multi-faceted and mammoth policy challenges. The category of regular wage salaried workers is heterogeneous, and includes jobs that are permanent, well paid with benefits, and are in the formal sector. Several of these workers

[21] Cyprus, Estonia, and the Czech Republic.

[22] For Spain, De la Rica *et al.* (2008) explained the sticky floor effect for workers with low education using a similar argument.

are unionized and work in jobs that are likely to be governed by labor laws, which include anti-discrimination provisions. Thus, in several aspects, this section of workers is likely to have better outcomes than those in casual work or those at the lower end of self-employment. If gender discrimination is high and persistent within this category of workers, among those with more precarious forms of work, gender discrimination is likely to be much worse. This paper presents a first focused snapshot of this sector in order to pave the way for further research which could explore demand-side factors, and the possible role of labor laws in mitigating discrimination.

It is clear that increasing female labor force participation, increasing women's share in regular wage jobs, and lowering labor market discrimination such that women earn wages commensurate with their qualifications constitute three equally urgent and important policy objectives. Given the evidence from across the globe between women's participation in economic work and higher economic growth, purely from an instrumental point of view, Indian economy would benefit immensely if these three objectives are followed seriously. Going beyond the instrumental view of women's work, the potential benefits of these objectives are immense as these are essential ingredients to achieving women's empowerment and gender equality.

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