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A Distributional Analysis of the Gender Wage Gap in Bangladesh*

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Abstract

This paper decomposes the gender wage gap along the entire wage distribution into an endowment effect and a discrimination effect, taking into account possible selection into full-time employment. Applying a new decomposition approach to the Bangladesh Labour Force Survey (LFS) data we find that women are paid less than men every where on the wage distribution and the gap is higher at the lower end of the distribution. Discrimination against women is the primary determinant of the wage gap. We also find that the gap has widened over the period 1999 - 2005. Our results intensify the call for better enforcement of gender based affirmative action policies.

Key Words: Gender wage Gap, Discrimination Effect, Selection, Unconditional Quantile Regression, Bangladesh
JEL Codes: C21, J16, J24, J31, J71

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1 Introduction

There now exists an extensive literature that analyses the extent of gender gap in wages. The specific aim of this literature is to try and understand whether the gap can be explained by differences in productive characteristics (the *endowment effect*) or by discrimination, where the gender gap in wages persists even after the differences in endowments have been controlled for (the *discrimination effect*). This is an important question from a policy perspective as different implications and policy prescriptions need to be drawn depending on the source of the wage gap.

The most common method of decomposing the gender wage gap in wages has been to use the Oaxaca-Blinder decomposition method (see Oaxaca, 1973; Blinder, 1973), which typically conducts the decomposition analysis at the mean of the wage distribution. However looking at the effect at the mean might not tell us the full story and recent evidence using data from both developed and transitional economies suggests that the average wage gap and decomposition at the mean is not representative of the gaps (and factors) that explain these gaps at different points of the wage distribution for the population of interest. See, for example, Albrecht, Bjorkluud, and Vroman (2003), Machado and Mata (2005), Miller (2005), Gupta, Oaxaca, and Smith (2006), Arulampalam, Booth, and Bryan (2007). One interesting conclusion from this line of research is that gender wage gap exists at the two extremes of the distribution of wages and most of these studies point to gender differences in the propensity to participate in the labour market. This implies that to obtain unbiased estimates of the gender wage gap, we need to explicitly account for self-selection into employment. For example, if women who stay out of employment are those who would have received the lowest returns from work then ignoring the selection issue would result in a significant bias in the estimated gender wage gap across the wage distribution.[1]

Although there is a sizeable literature using data from developed countries on decomposing the gender wage gap at different points of the wage distribution, the corresponding literature is relatively scarce for developing countries. Exceptions are Pham and Reilly (2007) for Vietnam,

[1]Indeed, Albrecht, Vuuren, and Vroman (2009) using data from Netherlands and Picchio and Mussida (2010) using data from Italy find that after adjusting for sample selection and for gender differences in the distribution of characteristics the average log-wage gap between male and female workers widens across the entire distribution of wages.

Ganguli and Terrell (2005) for Ukraine, and Nopo (2006) for Chile. None of these control for selection into employment, which is particularly relevant for developing countries, where the employment rate, the type of employment, and the choice of industry and occupation vary systematically by gender. One of the principal aims of this paper is to address this shortcoming by examining the extent of gender wage gap among employees who work full-time and also decompose this gap at different points of the distribution. It is unlikely that the sample of full-time workers represents a random draw from the population as a whole. It is suggested that only individuals with wages exceeding reservation wages will enter the labour market, and these individuals may have attributes (e.g., relative productivity in labour market and home activities, identity and life-cycle stage, and the attitudes and aspirations towards full-time work) that distinguish them from other individuals (working part-time, self-employed or not employed). If such factors are observable, then they can be included in the regression model and this will allow us to correct for the potential bias. However, the possibility that unobservable factors influence selection into full-time employment remains an obstacle.

In this paper, we use two nationally representative unit record data sets (surveys conducted in 1999-00 and 2005-06) from Bangladesh to examine the following questions:

1. Does the gender wage gap vary over the entire wage distribution?
2. What might cause the observed gender wage gaps to vary over the wage distribution?
3. Did the gender wage gap change over time?
4. How are the results affected if we explicitly take selection into full-time employment into account?

We start by conducting the standard Oaxaca-Blinder decomposition at the mean. This provides a useful benchmark, against which the extent of the gender wage gap at other points of distribution can be compared. The analytical framework that we adopt to compute and decompose the gender wage gap along the wage distribution is based on newly developed unconditional quantile regression models (see Firpo, Fortin, and Lemieux, 2009). The advantage of the unconditional quantile regression over the traditional conditional quantile regression approach is that its estimated coefficients can be explained as the impact of changes in the distribution of explanatory variables on the targeted quantiles of the unconditional marginal distribution of the dependent variable. Therefore, we can apply the Oaxaca-Blinder decomposition method directly to the estimation results from the unconditional quantile regressions. More detailed explanations of the unconditional quantile regression method that we use in this paper are provided in subsequent sections.

To investigate whether the gender wage gap varies over time, we conduct a decomposition analysis of changes in the gender wage gap along the wage distribution between two points in time (1999 and 2005). Several studies have shown that the factors that explain a gap do not necessarily explain changes in this gap over time and factors that are relevant in explaining changes at the lower tail of the wage distribution may be not relevant at the upper end (see Kassenbohmer and Sinning, 2010, for a survey). We extend the procedure proposed by Wellington (1993) who decomposes changes in the gender wage gap at the mean to decompose changes in the gender wage gap over the entire distribution of wages.[2]

This paper adds to the existing literature in a number of different ways. First, we perform decomposition across the entire distribution of wages, while emphasizing the sample selection issue. Second, we decompose changes in the gender wage gap between the two time periods to assess the changes in the contribution of individual covariates over time. Third, our distributional analysis is based on an unconditional quantile regression based model. We extend this new approach to take account of selectivity bias. We do this using the Heckman (1979) two-step approach and extend the Blinder-Oaxaca type decomposition to the unconditional quantile regression framework. To the best of our knowledge this is the first attempt of using the unconditional quantile regression model where the issue of selection bias is addressed explicitly. While acknowledging these methodological contributions, our focus is primarily on the decomposition of the gender wage gap at different points of the wage distribution.

We find that the extent of the gender wage gap varies significantly across the wage distribution after adjusting for gender differences in the distribution of characteristics, indicating that mean gender wage gap disguises the variation across the wage distribution. These differences

[2]There are a number of alternatives available to measure the change in the gender wage gap over time (see for example Smith and Welch, 1989). We use the Wellington (1993) approach, partly because of its simplicity.

are not uniform across the wage distributions; the disparity is largest in the lowest quantile (reaching 65% in 1999 and 108% in 2005 using real hourly wages) and declines (though not monotonically) as we go up the wage distribution. Differences in characteristics (the endowment effect) are not uniform at all quantiles and are mostly in favour of males. Discrimination explains the major proportion of the wage gap at all quantiles. The gender wage gap, however, increased over the period $1999-2005$ by about 26% at the lowest quantile and by about 20% at the highest quantile. Finally, sample selection into full-time employment has a significant impact on the gender wage gap and the results suggest that not controlling for sample selection is likely to over-estimate the observed wage gap.

2 Background Information and Literature

During the 1990's Bangladesh embarked on an ambitious program of economic reforms (political democratisation, macroeconomic stabilisation and trade liberalisation). During this period Bangladesh has experienced an accelerated GDP growth rate in real terms, with the growth rate increasing from 3.9% per annum in 1991 to 5.9% per annum in 1999 and further to 6.6% percent per annum in 2005. It is hardly a coincidence that a switch to a higher growth regime in the second half of the 1990's happened concurrently with the implementation of economic reforms. While there might be disagreements as to the extent to which this economic growth contributed to higher standard of living of the poor throughout this period, poverty rates (measured by consumption) declined from 50% in 1999 to 40% in 2005 (Sasin, 2007). It has been argued that the much of this poverty reduction was driven by an increase in wages and employment opportunities particularly in the non-agricultural sectors.

From a gender viewpoint, women have made important advances in the labour market during this period. Although still far behind that of men, women's labour force participation rate has increased from 23.9% in 1999 to 29.2% in 2005. This has been associated with an increased share of women in the urban labour force, particularly participation in manufacturing employment (often in the ready-made garments industries). But this increase has not been enough and gender inequalities continue to persist in the labour markets in Bangladesh. Women workers are still heavily concentrated in rural areas (employed in low productivity daily work for poor wages and often concentrated in public food for work programs) and in unpaid family businesses. On the contrary, despite a strong convergence in the distribution of characteristics (for example in terms of educational attainment) over the period $1999 - 2005$, wages of men and women have not converged to the same extent and a sizeable gender gap persists.[3] This is possibly a reflection of discrimination that women face at work.

The theoretical framework of this paper is based on *neoclassical economic theory* where labour markets are perfectly competitive and there is homogeneity and perfect substitutability of the labour force. Therefore, in a perfectly competitive market, discrimination originates from employer prejudice (Becker, 1971). This theoretical approach suggests that even in the presence of equal endowments of productive skills, wage inequality persist if employers reward productive skills differently depending on the gender of the worker. Such potential cause of wage inequalities is usually attributed to discrimination at the workplace.

Empirical studies that attempt to estimate the portion of the male-female wage differential associated with the *discrimination effect* in Bangladesh are fairly limited (Akter, 2005; Al-Samarrai, 2007; Kapsos, 2008; Ahmed and Maitra, 2010). While these studies differ substantially in terms of the period under consideration and also in terms of the data set used, they typically find that wage gap stems from discrimination, but estimates of its extent vary significantly. However, the existing literature considers only average wage differentials, neglecting the remainder of the distribution. Such a narrow focus is only justified if the earnings differential and the portion of the gap attributable to productivity differences is uniform across the distribution.

3 Empirical Methodology

3.1 Oaxaca-Blinder Decomposition

As a first attempt to formally identify the underlying causes of the gender wage gap, we perform an Oaxaca-Blinder decomposition at the mean. Specifically, we start by estimating

[3]For example, the proportion of female workers who have completed post-secondary schooling rose from 10% in 1999 to 17% in 2005. The corresponding proportions for male workers were 13% and 14% respectively.

separate (log) hourly wage equations for males and females as follows[4]:

$$\ln w_{ijt} = X'_{ijt}\beta_{jt} + \epsilon_{ijt}; i = 1, \ldots, n; j = m, f; t = 1999, 2005 \quad (1)$$

where i denotes the individual; j the gender group (male or female) and t the survey year (1999 or 2005); $\ln w_{ijt}$ is the log of hourly wages; X_{ijt} is the vector of explanatory variables (set of individual characteristics) that affect the wages received and ϵ_{ijt} is a vector of random error term with zero mean and constant variance. Equation (1) is estimated using OLS.

Define D_t as the difference in the expected value of male and female wages in period t (raw difference) obtained by estimating equation (1) separately for males and females. D_t can be decomposed into the component of the raw difference attributable to differences in observed characteristics or endowments (E) and to differences in coefficients (C). We can then write

$$\begin{aligned} D_t &= \overline{\ln w_{mt}} - \overline{\ln w_{ft}} = E + C = [\bar{X}'_{mt}\hat{\beta}_{mt} - \bar{X}'_{ft}\hat{\beta}_{ft}] \\ &= (\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt} + \bar{X}'_{ft}(\hat{\beta}_{mt} - \hat{\beta}_{ft}) \quad (2) \end{aligned}$$

where $\hat{\beta}_{jt}$ is the estimated value of β_{jt}. The first term in the right hand side of equation (2) $[(\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt}]$ is the explained component of the wage gap, which is the component of the gap that can be explained by differences in observed characteristics at the mean, weighted by coefficients attributable to men ($\hat{\beta}_{mt}$). This is E. For example, if women's relative endowment with human capital rises, the wage gap will decrease. The endowment effect then is negative.The second term $[\bar{X}'_{ft}(\hat{\beta}_{mt} - \hat{\beta}_{ft}]$ is the unexplained component. This is C. It is the difference in the return to observable characteristics of males and females, evaluated at the mean set of the female's characteristics and is interpreted as an estimate of labour market discrimination after adjusting for differences in observable characteristics.

An alternative way of writing equation (2) is to use the female wage structure as the reference category. In this case, the explained component can be written as $(\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{ft}$ and the unexplained component can be written as $\bar{X}'_{mt}(\hat{\beta}_{mt} - \hat{\beta}_{ft})$. We present and discuss the results

[4]Wage equations are estimated separately for men and women in order to allow for different rewards by gender to a set of productive characteristics or endowments. A Chow test rejects the null hypothesis that explanatory variables have equal impacts on the wage rates of males and females for both years. The Chow test statistics for survey year 1999 is $F(35, 5451) = 12.21$ (with a $p - value = 0.000$), and $F(35, 18322) = 37.12$ (with a $p - value = 0.000$) for the survey year 2005.

corresponding to the case where the male wage rate is the reference category. The results using the female wage rate as the reference category are available on request.[5]

It is, however, important to note that the entire unexplained portion cannot be attributed to discrimination alone as it might also capture the impact of model misspecification, omitted variables and measurement error. This latter issue might mean that the different outcomes for men and women may be the result of differences of some unobserved variables (for example, motivation, congeniality, ability to work in a group, sensitivity etc.) that are not captured by variables included in the analysis.

3.2 Distributional Decomposition using Unconditional Quantile Regressions

This section expands our analysis by examining the gender wage gap along the whole distribution of wages using a Blinder-Oaxaca type decomposition approach based on unconditional quantile regression estimates (see Firpo, Fortin, and Lemieux, 2009). They show that a corresponding Blinder-Oaxaca type decomposition can be approximated for any distributional statistic (including quantiles). This method comprises of two stages. In the first stage, distributional changes are divided into a wage structure effect and a composition effect using a re-weighting method. The re-weighting method allows us to directly estimate these two components without having to estimate a structural wage setting model. In the second stage, the two components are further divided into the contribution of each explanatory variable using re-centred influence function (RIF) regressions. These regressions directly estimate the impact of the explanatory variables on the distributional statistic of interest thereby generalising the Oaxaca-Blinder decomposition method by extending the decomposition to any

[5] In doing so, we have abstracted from an important debate: which wage structure should we use as the reference category? The Blinder-Oaxaca method applied both male and female wage structures as the reference category. This creates an index number problem, since the estimates of the discrimination component differs depending on the choice of the reference category. Further, the resulting levels of discrimination provide a range within which the actual level of discrimination falls. Reimers (1983) hypothesizes that the correct procedure is instead to take an average of both male and female wage structures. Cotton (1988) suggests improving upon the procedure by employing a weighted average of the two wage structures, which should then provide us with an exact figure rather than a range. Neumark (1988), on the contrary, regards these benchmarks as unsatisfactory and argues that the choice of a non-discriminatory wage structure should be based on the OLS estimates from a pooled regression (of both males and females). However, Ginther and Hayes (2003) point out that pooled wage structure (i.e., average of the male and female wage structures) is not likely to be used in legal framework concerned with equal opportunities for women and men. Rather the authors argue that men are the usual comparison group in legal proceedings concerning gender discrimination.

distributional measure. Specifically the predicted wage differential $D_t(\nu)$ measured in terms of quantile ν can be decomposed as follows:

$$
\begin{aligned}
D_t(\nu) &= \ln w_{mt}(\nu) - \ln w_{ft}(\nu) = E(\nu) + C(\nu) \\
&= [\bar{X}'_{mt}\hat{\beta}_{mt}(\nu) - \bar{X}'_{ft}\hat{\beta}_{ft}(\nu)] \\
&= (\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt}(\nu) + \bar{X}'_{ft}[(\hat{\beta}_{mt}(\nu) - \hat{\beta}_{ft}(\nu)]
\end{aligned} \tag{3}
$$

Here $\hat{\beta}_{jt}(\nu)$ is the parameter estimates of the re-centred influence function (RIF) regression model, $\bar{X}_{jt}$ is a vector of average characteristics of workers.[6] In our analysis we apply this framework to the following quantiles $\nu = 0.10, 0.25, 0.50, 0.75, 0.90$ in order to obtain the unconditional quantile regression estimates.

3.3 Decomposition of the Inter-temporal Change in the Gender Wage Gap

We use the Wellington (1993) method to extend the single period Oaxaca-Blinder approach to analyse changes in the wage gap over time. We want to examine how the changes in the characteristics and the returns to these characteristics combine to affect the gender wage gap over the relevant period. To do this, we start by subtracting the difference in log wages in period τ from the corresponding difference in period t. Specifically we can write the change in the mean gender wage gap over time as follows:

$$
\begin{aligned}
D_t - D_\tau &= [\bar{X}'_{mt}\hat{\beta}_{mt} - \bar{X}'_{ft}\hat{\beta}_{ft}] - [\bar{X}'_{m\tau}\hat{\beta}_{m\tau} - \bar{X}'_{f\tau}\hat{\beta}_{f\tau}] \\
&= [(\bar{X}_{mt} - \bar{X}_{m\tau})'\hat{\beta}_{mt} - (\bar{X}_{ft} - \bar{X}_{f\tau})'\hat{\beta}_{ft}] \\
&+ [\bar{X}'_{m\tau}(\hat{\beta}_{mt} - \hat{\beta}_{m\tau}) - \bar{X}'_{f\tau}(\hat{\beta}_{ft} - \hat{\beta}_{f\tau})]
\end{aligned} \tag{4}
$$

where $D_t = \overline{\ln w_{mt}} - \overline{\ln w_{ft}}$. The first term of the decomposition $[(\bar{X}_{mt} - \bar{X}_{m\tau})'\hat{\beta}_{mt} - (\bar{X}_{ft} - \bar{X}_{f\tau})'\hat{\beta}_{ft}]$ shows the change in the wage gap due to changes in the mean of the regressions (the explained portion) evaluated at the period t coefficients. The second term $[\bar{X}'_{m\tau}(\hat{\beta}_{mt} - \hat{\beta}_{m\tau}) - \bar{X}'_{f\tau}(\hat{\beta}_{ft} - \hat{\beta}_{f\tau})]$ represents the portion of the change in the wage gap that can be explained by

[6] We follow Garcia, Hernandez, and Lopez-Nicolas (2001) and Mueller (1998) and use average characteristics to decompose the wage differentials at different quantiles.

changes in the coefficients between the two periods, evaluated at the corresponding group's mean in period τ.

We can extend equation (4) to decompose the wage difference at the different quantiles over time as:

$$\begin{aligned} D_t(\nu) - D_\tau(\nu) &= [\bar{X}'_{mt}\hat{\beta}_{mt}(\nu) - \bar{X}'_{ft}\hat{\beta}_{ft}(\nu)] - [\bar{X}'_{m\tau}\hat{\beta}_{m\tau}(\nu) - \bar{X}'_{f\tau}\hat{\beta}_{f\tau}(\nu)] \\ &= [(\bar{X}_{mt} - \bar{X}_{m\tau})'\hat{\beta}_{mt}(\nu) - (\bar{X}_{ft} - \bar{X}_{f\tau})'\hat{\beta}_{ft}(\nu)] \\ &+ [\bar{X}'_{m\tau}(\hat{\beta}_{mt}(\nu) - \hat{\beta}_{m\tau}(\nu)) - \bar{X}'_{f\tau}(\hat{\beta}_{ft}(\nu) - \hat{\beta}_{f\tau}(\nu))] \end{aligned} \tag{5}$$

Changes in any of these above components over time would cause changes in the gender wage gap. In terms of mean characteristics, the explanations centre around changes in male-female productivity related characteristics. For example, if women's work experience over time becomes similar to that of men's, then the male-female wage gap is likely to be reduced. On the other hand, there might be a number of different reasons as to why differences in the coefficients might change over time. For example, if there are changes in the returns to the explanatory variables, such as a change in the relative magnitudes of the coefficients that favour women, there will be a reduction in the gender wage gap.

4 Data and Descriptive Statistics

The data sets used in our analysis comes from Bangladesh, specifically from two Labour Force Surveys conducted in $1999-2000$ (hence forth LFS 1999) and $2005-2006$ (hence forth LFS 2005). These are nationally representative (cross-sectional) random samples, administered by the Bangladesh Bureau of Statistics. The questionnaires for the two surveys is almost identical, and therefore overall inter temporal compatibility is very good. The data contains information on a range of individual (age, gender, marital status, educational attainment, employment status, hours worked, wages earned) and household level characteristics (household size and composition, religion, land holding, location, asset ownership). However the big difference in the two data sets is in terms of the sample size.

The estimating sample for the LFS 1999 data set consists of 12652 individuals from 9790 households, while that for the LFS 2005 data set consists of 57074 individuals from 40000 households. The main reason for this large difference in sample sizes is the extent of coverage: while the LFS 1999 consists of 442 Primary Sample Units (PSUs), of which 252 are rural and the rest are urban, the LFS 2005 is conducted in 1000 PSUs of which 640 are in rural areas and the rest are in the urban areas. From each PSU, 40 households were randomly selected for a detailed interview in the LFS 2005 while only 20 households from each rural PSU and 25 from each urban PSU were randomly selected for the same in LFS 1999.

Our decomposition analysis is restricted to individuals aged $15-65$ who are in full-time wage employment (specifically defined as individuals who work for 40 hours or more during the week).[7] We exclude child workers, unpaid domestic workers, the disabled and full-time students from our analysis. The selected sample of full-time workers consists of 5522 individuals (84% males) in the LFS 1999 data set and 18392 individuals (88% males) in the LFS 2005 data set.

In the wage regression the dependent variable is the log of hourly wages. Hourly wages is computed by dividing monthly wages by the total hours of work per month. The survey collected information on the usual hours work per week but not the number of weeks worked during a month. Therefore the monthly hours of work is computed by multiplying the usual hours of work per week by 4.3. All nominal wages are converted to real values using the national consumer price index, $1999 = 100$.

Figure 1 presents the distribution of wages by gender for the two survey years. The mass of the distribution of wages for males is to the right of that for females. Figure 2 shows that the distribution of wages has shifted to the right for both males and females in 2005, relative to 1999. A more detailed picture of this evolution of wage rates of males and females and gender wage gaps over the period $1999-2005$ could be seen from Table 1, which presents the log real hourly wages and the gender wage gap at the different quantiles and at the mean for the two data sets. The estimated (log) real hourly wages for both males and females increased over the period $1999-2005$. The increase in wage rates is more relevant for men than for women. This is true at the mean as well as at the different quantiles. In addition, the gender wage gap

[7] The official retirement age in Bangladesh is 60 for males and 55 for females. However these retirement ages are enforced only in the public sector and a large proportion of men and women continue to work into their 60's.

has increased over the relevant period almost every where on the distribution. The increase in the gender wage gap has been greater at the lower end of the distribution, increasing from 0.5026 log points in 1999 to 0.7303 log points in 2005 at the 10^{th} quantile ($\nu = 0.10$) compared to the upper end of the distribution, where it has increased from 0.2261 log points in 1999 to 0.4049 log points in 2005 at the 90^{th} quantile ($\nu = 0.90$).

In addition to the differences in the (log) real hourly wages between males and females discussed above, there are substantial differences in the means of the observed characteristics. Gender specific descriptive statistics over the sample of the total population are presented in Table 2. Table 3 presents instead descriptive statistics for the sample of full-time wage employees (the *selected* sample). We also present t-tests for gender differences.

Table 2 shows that more than 40% of men and women are likely to be in full-time wage employment in 1999, and the gender difference is not statistically significant. However, full-time wage employment has decreased for both males and females over the period $1999-2005$. For men this decline is 14% (down from 43% in 1999 to 37% in 2005), while for women this decline is 62% (down from 45% in 1999 to 17% in 2005). Females are on an average younger and are generally less educated than males. Gaps in educational attainment between males and females are statistically significant at all levels of education over the period $1999-2005$. A higher proportion of males are married in 1999 when compared to females and interestingly this pattern is reversed in 2005.

Restricting ourselves to the sample of full-time wage employees (Table 3), we again find that women are in general younger, and are more likely to be in full-time employment if they reside in the urban region. The gender difference is statistically significant in each of the two survey years. Moreover, females are generally less educated except at the Post Secondary and Graduate levels in 2005 and the gender differences is statistically significant at the 1% level. Women are predominantly employed in production related jobs whereas men dominate agriculture related occupation.[8]

[8] We have included seven occupation categories corresponding to International Standard Classification of Occupation (ISCO-88) and ten industries indicators according to Bangladesh Standard Industrial Classification (BSIC, Rev-3).These industry and occupation controls might embody unmeasured industry-specific and occupation-specific human capital (Arulampalam, Booth, and Bryan, 2007). Therefore, we may overlook the potential effect of unobserved human capital if we exclude such controls from the analysis. Estimates with such controls can be viewed as a lower bound of the extent of discrimination.

5 Results

5.1 Decomposition Results Without Selection Correction

We start by a discussion of the results of the decomposition at the mean.[9] This forms an interesting baseline to which the results for the rest of the distribution can be compared. Table 4 presents the decomposition results (specifically the proportion of the total wage gap that is attributable to discrimination) at the mean for the two survey years. The results that are presented use male wages as the reference category. The results using females wages as the reference category are similar and are available on request. Decomposition of the OLS estimates reveals that in 1999 the wage difference between males and females, when male wages is the reference category is 0.4542 log points, which corresponds to a wage differential of $(\exp(0.4542) - 1) \times 100 = 57\%$. Decomposition of this gap reveals that the explained component is considerably smaller compared to the component due to discrimination and after accounting for differences in productive characteristics, the discrimination component is 93% of the total wage gap and only 7% of the total wage gap is explained by the *superior endowment* of the male. The wage gap between males and females increases to 0.6488 log points (91%) in 2005. Compared to the results for 1999, we find that while the discrimination component (as a proportion of the total wage gap) is lower in 2005, discrimination continues to account for the majority of the observed wage gap. See Table A-1 for more details of the decomposition.

The decomposition results based on the unconditional quantile regressions by survey year are also presented in Table 4. We find that for both surveys, the estimated total gender wage gap is higher at the lower end of the distribution, compared to the higher end. The gender wage gap is systematically higher for the 2005 sample compared to the 1999 sample, with the gap ranging from $25 - 72\%$ in 1999 to $50 - 133\%$ in 2005. Notice that the wage gap is lower at the 90^{th} quantile of the wage distribution compared to anywhere else on the distribution. For both survey years and everywhere on the distribution, discrimination accounts for the majority of the gender wage gap, ranging from 77% at the 90^{th} quantile to 101% at the median in 1999

[9] The wage regression estimates, using the mean and the unconditional quantile regression models, are not presented. They are however available on request. The set of explanatory variables included in X in both types of models are age, educational attainment, training, marital status, region of residence and occupation and industry codes.

and from 73% at the 25^{th} quantile to 104% at the 90^{th} quantile in 2005. However with the exception of the 90^{th}quantile, the proportion of the gender wage gap due to discrimination is lower for the 2005 sample, compared to the 1999 sample.

Turning to the contribution of different characteristics (*endowments*) of men and women as a proportion of the wage gap reveals that differences in characteristics mostly are in favour of males both at the bottom and top end of wage distribution. While making up about 17% at the lower end of the distribution, it accounts 23% between high earnings women and their male counterparts in 1999, highlighting the relevance of the *endowment* effect at the upper end of the wage distribution.[10] The pattern changes slightly in 2005, while the contribution of characteristics (*endowments*) is in favour of males at the lower tail of wage distribution, it changed in favour of females at the 90^{th}quantile. Thus improvement in observed characteristics over time among high earning women tended to reduce gender gap but discrimination against them completely wiped out these gains.

We next turn to the decomposition of the change in wages over the period $1999 - 2005$, using the 2005 wage coefficients as the reference category.[11] These results are presented in Table 5. Almost every where (the exception being the 75^{th} quantile), the wage gap has increased over the relevant period: from 36% at the 25^{th} to 20% at the 90^{th} quantile). What is interesting is that at the lower end of the wage distribution ($\nu = 0.10, 0.25, 0.50$), the endowment effect is actually negative, indicating that if wages were to be determined only by endowments and observable productive characteristics, the total wage gap should actually decrease at the lower end of the distribution.[12] Discrimination against women however completely wiped out these beneficial effects arising from changes in productive characteristics.

At the upper end of the distribution ($\nu = 0.90$), however less than 30% of the change in total wages is explained by discrimination. This result appears to suggest that once women have reached a position where they are at the higher end of the wage distribution, they do not face significant discrimination; i.e., the male premium is not particularly high at the upper end of the wage distribution (see Table 4). This could also be related to selection - women whose

[10]See Table A-1 for the contribution of the different explanatory variables used in the regression analysis.

[11]The choice of the reference category is arbitrary. An alternative decomposition could be obtained by taking the 1999 wage coefficients as the reference category.

[12]The most striking finding is changes in educational attainment in favour of women that helps to reduce the wage gap. The results are not shown here but are available on request.

earnings place them at the higher end of the wage distribution might not be a random subset of the sample of women. We next turn to this issue of selection.

5.2 Selection into Employment?

In the results presented in Section 5.1, wage equations were estimated for the sample of full-time workers. There could be a significant sample selection bias here as full-time employees might not be a random subset of all workers but differ systematically, in unobservable aspects of preferences, opportunities, and productivity, from those not employed, self-employed or employed on a part-time basis. The issue of selection into full-time employment is of particular concern in this paper because a significant proportion of the sample is self-employed (about 50%) and working in family businesses (7%), with self-employment is more common among men. One way to correct this selection bias is to employ standard Heckman two-step estimation technique.We first estimate the Inverse Mill's Ratio (λ) from a probit equation determining full–time participation in the labour market (choosing to become a full–time wage employee). This is done by estimating the following equation

$$I_{ijt} = Z'_{ijt}\gamma_{jt} + u_{ijt}; i = 1, \ldots, n; j = m, f; t = 1999, 2005 \tag{6}$$

where I_{ijt} is a dummy variable denoting full-time employment status ($I = 1$ if the individual is in full-time employment and 0 otherwise) and $u_{ijt} \sim IIDN(0, 1)$.[13] Estimation of equation (6) allows us to compute the Inverse Mill's Ratio (λ), which is then added as an additional regressor in equation (1), both at the mean and the different quantiles. We include ownership of dwelling (home ownership), wealth quintile of the household, number of young children in the household and number of men and women in the household over 65 years of age as identifying variables. These variables are assumed to affect the probability of full-time employment but not to affect wages: indeed, there is very little reason to expect that these variables will have an effect on the wage rate, which is market determined (and is typically beyond the control of any individual).

We can now compute the extended gender wage gap (at the mean) as

$$D_t = \overline{\ln w_{mt}} - \overline{\ln w_{ft}} = (\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt} + [\bar{X}'_{ft}(\hat{\beta}_{mt} - \hat{\beta}_{ft})] + (\hat{\theta}_{mt}\bar{\lambda}_{mt} - \hat{\theta}_{ft}\bar{\lambda}_{ft}) \tag{7}$$

[13]Estimation of equation (6) uses data on 12652 individuals (84% males) for LFS 1999 and 57074 individuals (77% males) for LFS 2005.

where $(\hat{\theta}_{mt}\bar{\lambda}_{mt} - \hat{\theta}_{ft}\bar{\lambda}_{ft})$ is the contribution of differences in the average selectivity bias.[14] Selectivity bias results in the observed wage differential being different from the offered wage differential. If we re-write equation (7) as:

$$D_t = (\overline{\ln w_{mt}} - \overline{\ln w_{ft}}) + (\hat{\theta}_{ft}\bar{\lambda}_{ft} - \hat{\theta}_{mt}\bar{\lambda}_{mt}) = (\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt} + [\bar{X}'_{ft}(\hat{\beta}_{mt} - \hat{\beta}_{ft})] \qquad (8)$$

then the left hand side of equation (8) provides a measure of differences in the offered wage (the sum of the difference in the observed mean wages and the difference in average selectivity bias).[15] The only difference between equations (7) and (8) is that equation (8) presents a decomposition of the selectivity adjusted wage difference (difference in offered wages) as opposed to a decomposition of the observed wage difference, as in equation (7). Equation (8) can be estimated at different quantiles.

The decomposition of the change in the gender wage gap (at the mean) over time taking into account selection into full-time employment can be computed as:

$$\begin{aligned}
D_t - D_\tau &= [\bar{X}'_{mt}\hat{\beta}_{mt} - \bar{X}'_{ft}\hat{\beta}_{ft}] - [\bar{X}'_{m\tau}\hat{\beta}_{m\tau} - \bar{X}'_{f\tau}\hat{\beta}_{f\tau}] \\
&= [(\bar{X}_{mt} - \bar{X}_{m\tau})'\hat{\beta}_{mt} - (\bar{X}_{ft} - \bar{X}_{f\tau})'\hat{\beta}_{ft}] \\
&+ [\bar{X}'_{m\tau}(\hat{\beta}_{mt} - \hat{\beta}_{m\tau}) - \bar{X}'_{f\tau}(\hat{\beta}_{ft} - \hat{\beta}_{f\tau})] \\
&+ \left[\left(\bar{\lambda}_{mt} - \bar{\lambda}_{m\tau}\right)' \hat{\theta}_{mt} - \left(\bar{\lambda}_{ft} - \bar{\lambda}_{f\tau}\right)' \hat{\theta}_{ft}\right] \\
&+ \left[\bar{\lambda}'_{m\tau}\left(\hat{\theta}_{mt} - \hat{\theta}_{m\tau}\right) - \bar{\lambda}'_{f\tau}\left(\hat{\theta}_{ft} - \hat{\theta}_{f\tau}\right)\right] \qquad (9)
\end{aligned}$$

We can decompose the gender wage gap at different points of the wage distribution taking into account sample selection as follows:

$$\begin{aligned}
D_t(\nu) =& (\ln w_{mt}(\nu) - \ln w_{ft}(\nu)) + (\hat{\theta}_{ft}(\nu)\bar{\lambda}_{ft} - \hat{\theta}_{mt}(\nu)\bar{\lambda}_{mt}) \\
=& (\bar{X}_{mt} - \bar{X}_{ft})'\hat{\beta}_{mt}(\nu) + [\bar{X}'_{ft}(\hat{\beta}_{mt}(\nu) - \hat{\beta}_{ft}(\nu))] \qquad (10)
\end{aligned}$$

Finally we can extend equation (9) to decompose the wage differences between men and

[14] λ_{jt} is the Inverse Mill's Ratio, included as an additional explanatory variable in the wage equation. $\hat{\theta}_{jt}$ is the estimated coefficient of λ_{jt} from this regression.

[15] See Duncan and Leigh (1980) and Reimers (1983).

women over time at different quantiles in presence of selection as.

$$
\begin{aligned}
D_t(\nu) - D_\tau(\nu) &= [\bar{X}'_{mt}\hat{\beta}_{mt}(\nu) - \bar{X}'_{ft}\hat{\beta}_{ft}(\nu)] - [\bar{X}'_{m\tau}\hat{\beta}_{m\tau}(\nu) - \bar{X}'_{f\tau}\hat{\beta}_{f\tau}(\nu)] \\
&= [(\bar{X}_{mt} - \bar{X}_{m\tau})'\hat{\beta}_{mt}(\nu) - (\bar{X}_{ft} - \bar{X}_{f\tau})'\hat{\beta}_{ft}(\nu)] \\
&+ [\bar{X}'_{m\tau}(\hat{\beta}_{mt}(\nu) - \hat{\beta}_{m\tau}(\nu)) - \bar{X}'_{f\tau}(\hat{\beta}_{ft}(\nu) - \hat{\beta}_{f\tau}(\nu))] \\
&+ \left[\left(\bar{\lambda}_{mt} - \bar{\lambda}_{m\tau}\right)'\hat{\theta}_{mt}(\nu) - \left(\bar{\lambda}_{ft} - \bar{\lambda}_{f\tau}\right)'\hat{\theta}_{ft}(\nu)\right] \\
&+ \left[\bar{\lambda}'_{m\tau}\left(\hat{\theta}_{mt}(\nu) - \hat{\theta}_{m\tau}(\nu)\right) - \bar{\lambda}'_{f\tau}\left(\hat{\theta}_{ft}(\nu) - \hat{\theta}_{f\tau}(\nu)\right)\right] \qquad (11)
\end{aligned}
$$

How important is the selection effect? From Figure 3 it appears that the answer to this question depends on the sample and the quantile under consideration. For the sample of women the coefficient estimate of λ is positive and statistically significant at the mean in 2005 and never different from zero at the selected quantiles in both survey years. For males on the other hand, while the coefficient estimate of λ is positive and significant at the mean in both survey years, the coefficient estimate of λ is sometimes statistically significant at selected quantiles in both years. The results, however, suggest the contribution of the selection term (Inverse Mill's Ratio) to wage dispersion among employed males at the mean as well as at selected quantiles. Although the selection correction factor is not statistically significant for females across quantiles, for the sake of consistency we compute and present (in Tables 6 and 7) the decomposition results adjusted for sample selection bias.

The results at the mean in both survey years reveals that the differences in productive characteristics are in favour of males (Table 6). Although the discrimination component is the major component of the wage gap in 2005, it turns out to be negative in 1999. Using different datasets Akter (2005) and Ahmed and Maitra (2010) obtained similar results. However as with these papers, we are unable to provide any valid and consistent explanation for this negative discrimination effect.

The decomposition results using the selectivity corrected quantile regression model paints a rather different picture, particularly with respect to the discrimination effect. Women at the bottom and the top quantiles have benefited from reduced discrimination in 2005, going from -0.03 log points at the 10^{th}quantile to -0.349 log points at the 90^{th}quantile. As in the case for the mean gender wage gap, the selection effect is positive except at the 25^{th} quantile in

2005. Therefore, the observed wage gap needs to be adjusted downward to correct for sample selection bias. These results, however, should be interpreted cautiously as the selection control factor (Inverse Mill's Ratio) is not statistically significant for females throughout the wage distribution.

Turning next to decomposition results for the change in the wage gap over the period $1999 - 2005$ (Table 7), we see that inclusion of the selection term does not change the results in any significant manner. While women at the lower tail of the distribution and at the mean have benefited from changes in mean characteristics (e.g.,changes in educational attainment), women at the upper end of the distribution fell behind their male counterparts, the discrimination component appears to have actually worked in favour of females at the upper end of the wage distribution.

6 Concluding Comments and Policy Implications

The main objective of this paper is to examine whether the gender wage gap varies along the wage distribution. We also investigate whether the gender wage gap changes over time across the wage distribution to assess the contribution of different factors that may explain changes in the gender wage gap, both at the mean and also at other points of the distribution. Finally we consider the effects of sample selection (selecting into full-time employment for both males and females) on the gender wage gap at different points of the distribution of wages.

Our decomposition results indicate that women employees are paid less on average compared to their male counterparts over the period $1999 - 2005$ and the gap is greater at the lower end of the wage distribution compared to the upper end of the wage distribution. The major component of the wage gap is attributed to labour market discrimination against women and it is lower for high-wage earners than for low wage earners. However, the size of the *endowment* effect varies significantly over the period under consideration and is mostly in favour of men. Analyses of the changes in the gender wage gap by earnings percentile show that the gap widened much more at the lower end of the wage distribution than at the upper end over the study period. A sizeable part of the increase in the gender wage gap at the lower tail of the distribution is due to an increase in discrimination against females. Our results also show that not controlling for sample selection is likely to over-estimate the observed wage gap across the wage distribution. The selection corrected wage gap (the offered wage gap) is explained almost entirely by discrimination against women.

What causes the gender wage gap and why is the gender wage gap more at the lower tail of the distribution? It is possibly the result of a combination of a number of different factors (for example trade unionism, social norms); unfortunately the available data does not allow us to elaborate on this question. We find that discrimination is a major part of the wage differential along the entire wage distribution. These facts strongly suggest that, although the Bangladesh labour code stipulates equal pay and equal employment opportunity, there is still potential underutilisation of women's skills in the labour market. While legislations have been passed and the legislature has accepted the role of gender based affirmative action policies in reducing the gender wage gap, there is considerable lack of enforcement of these laws. To attain true gender equality we need stronger enforcement.

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Table 1: Log Real Hourly Wages and Gender Wage Gap over the Different Quantiles

Quantile	Males			Females			Gender Wage Gap		
	1999	2005	2005 − 1999	1999	2005	2005 − 1999	1999	2005	2005 − 1999
0.10	1.3153	1.8276	0.5123	0.8126	1.0973	0.2847	0.5026	0.7303	0.2277
0.25	1.6308	2.5099	0.8791	1.0885	1.6625	0.5740	0.5423	0.8475	0.3052
0.50	2.0609	3.1321	1.0712	1.5920	2.4790	0.8870	0.4688	0.6530	0.1842
0.75	2.7350	3.4891	0.7541	2.1799	3.0143	0.8344	0.5551	0.4747	-0.0804
0.90	3.2210	3.8040	0.5830	2.9949	3.3990	0.4041	0.2261	0.4049	0.1788
Mean	2.1734	2.9727	0.7996	1.7192	2.3239	0.6047	0. 4542	0.6488	0.1946

The wage gap is measured as the difference between the log male real hourly wages and the log female real hourly wages.

Table 2: Descriptive Statistics: Full Sample

	LFS 1999					LFS 2005				
	Male		Female		Difference	Male		Female		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	t-test	Mean	Std. Dev.	Mean	Std. Dev.	t-test
Employment. Reference: Self employed or employed in family business										
Full-time Employment	0.4340	(0.4956)	0.4499	(0.4976)	-1.32	0.3684	(0.4824)	0.1712	(0.3767)	43.36***
Age. Reference Age 60 or higher										
Age 15 – 19	0.0863	(0.2808)	0.1603	(0.3669)	-10.21***	0.1037	(0.3049)	0.0422	(0.2011)	21.90***
Age 20 – 24	0.0926	(0.2898)	0.1780	(0.3826)	-11.39***	0.1148	(0.3188)	0.1489	(0.3560)	-10.50***
Age 25 – 29	0.1180	(0.3227)	0.1749	(0.3800)	6.99***	0.1230	(0.3284)	0.1705	(0.3761)	-14.15***
Age 30 – 34	0.1366	(0.3434)	0.1441	(0.3513)	-0.89	0.1223	(0.3276)	0.1504	(0.3575)	-8.49***
Age 35 – 39	0.1535	(0.3604)	0.1178	(0.3224)	4.11***	0.1381	(0.3450)	0.1508	(0.3579)	-3.71***
Age 40 – 44	0.1333	(0.3399)	0.0763	(0.2656)	7.06***	0.1186	(0.3233)	0.1156	(0.3197)	0.95
Age 45 – 49	0.1045	(0.3059)	0.0693	(0.2540)	4.82***	0.1070	(0.3091)	0.0892	(0.2850)	5.93***
Age 50 – 54	0.0770	(0.2666)	0.0430	(0.2028)	5.40***	0.0754	(0.2641)	0.0621	(0.2413)	5.20***
Age 55 – 59	0.0502	(0.2184)	0.0197	(0.1391)	5.99***	0.0508	(0.2197)	0.0392	(0.1940)	5.52***
Education. Reference: No Schooling										
Primary School	0.2381	(0.4259)	0.1901	(0.3925)	4.66***	0.2380	(0.4259)	0.2290	(0.4202)	2.14**
Secondary School	0.2051	(0.4038)	0.1663	(0.3725)	3.97***	0.2257	(0.4180)	0.1627	(0.3691)	15.64***
Post Secondary School	0.1236	(0.3291)	0.1036	(0.3049)	2.50***	0.1276	(0.3337)	0.0688	(0.2530)	18.81***
Graduate	0.0672	(0.2503)	0.0460	(0.2096)	3.54***	0.0568	(0.2314)	0.0300	(0.1705)	12.40***
Marital Status: Reference: Single										
Married	0.7983	(0.4013)	0.6466	(0.4781)	14.96***	0.7666	(0.4230)	0.8065	(0.3951)	-9.67***
Divorced	0.0011	(0.0335)	0.0369	(0.1886)	-18.12***	0.0017	(0.0414)	0.0244	(0.1543)	-27.67***
Widowed	0.0027	(0.0521)	0.1107	(0.3139)	-33.18***	0.0065	(0.0803)	0.0985	(0.2980)	-58.02***
Presence of Children. Reference: If household has no children										
Number of Children 0 – 5	0.7192	(0.8516)	0.6229	(0.7954)	4.67***	0.6283	(0.7693)	0.6399	(0.7999)	-1.51
Number of Children 6 – 12	1.0194	(1.0280)	0.9009	(0.9691)	4.75***	0.8517	(0.9426)	0.8931	(0.9725)	-3.45***
Home Ownership. Reference: If household owns an accommodation										
Household Pays No Rent	0.0292	(0.1685)	0.0551	(0.2282)	-5.90***	0.0191	(0.1367)	0.0236	(0.1518)	-3.27***
Household Pays Rent	0.2119	(0.4087)	0.3140	(0.4642)	-9.98***	0.0962	(0.2948)	0.0768	(0.2664)	6.78***
Region. Reference: Rural										

Continued on next page

Table 2 (continued): Descriptive Statistics: Full Sample

	LFS 1999					LFS 2005				
	Male		Female		Difference	Male		Female		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	t-test	Mean	Std. Dev.	Mean	Std. Dev.	t-test
Urban	0.5080	(0.0048)	0.6355	(0.0108)	-10.48***	0.4005	(0.4900)	0.3390	(0.4734)	12.79***
Number of Males 65 or Higher	0.0398	0.1974	0.0581	0.2362	-3.67***	0.0679	0.2521	0.0813	0.2736	-5.27***
Number of Females 65 or Higher	0.0318	0.1754	0.0298	0.1702	0.36	0.0626	0.2440	0.0571	0.2330	2.32***
Wealth Quintile. Reference: Quintile 1										
Quintile 2	0.2098	(0.4072)	0.1547	(0.3617)	5.62***	0.1885	(0.3911)	0.2105	(0.4076)	-5.61***
Quintile 3	0.2062	(0.4046)	0.1653	(0.3716)	4.18***	0.1964	(0.3972)	0.2106	(0.4078)	-3.61***
Quintile 4	0.1956	(0.3967)	0.2184	(0.4133)	-2.33**	0.2033	(0.4024)	0.1848	(0.3882)	4.67***
Quintile 5	0.1924	(0.3942)	0.2396	(0.4270)	-4.83***	0.2134	(0.4097)	0.1562	(0.3630)	14.49***

$*** : p < 0.01; ** : p < 0.05; * : p < 0.1$

Table 3: Descriptive Statistics: Sample in Full-Time Employment

	LFS 1999					LFS 2005				
	Male		Female		Difference	Male		Female		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	t-test	Mean	Std. Dev.	Mean	Std. Dev.	t-test
Age. Reference: 60 or higher										
Age 15 – 19	0.1021	(0.0044)	0.1382	(0.0116)	-3.18***	0.1150	(0.0025)	0.1229	(0.0069)	-1.11
Age 20 – 24	0.1025	(0.0046)	0.1708	(0.0126)	-5.89***	0.1168	(0.0025)	0.1330	(0.0071)	-2.24**
Age 25 – 29	0.1246	(0.0048)	0.1742	(0.0127)	-4.00***	0.1299	(0.0026)	0.1640	(0.0077)	-4.48***
Age 30 – 34	0.1414	(0.0051)	0.1562	(0.0122)	-1.15	0.1293	(0.0026)	0.1518	(0.0075)	-2.98***
Age 35 – 39	0.1524	(0.0053)	0.1393	(0.0116)	1.00	0.1426	(0.0028)	0.1514	(0.0075)	-1.11
Age 40 – 44	0.1317	(0.0050)	0.0798	(0.0091)	4.32***	0.1190	(0.0026)	0.1142	(0.0067)	0.67
Age 45 – 49	0.1021	(0.0044)	0.0809	(0.0091)	1.94*	0.1013	(0.0024)	0.0744	(0.0055)	4.05***
Age 50 – 54	0.0784	(0.0039)	0.0416	(0.0067)	3.88***	0.0717	(0.0020)	0.0464	(0.0044)	4.48***
Age 55 – 59	0.0784	(0.0039)	0.0416	(0.0067)	3.85***	0.0455	(0.0016)	0.0284	(0.0035)	3.75***
Education. Reference: No Schooling										
Primary School	0.2137	(0.4100)	0.1843	(0.3879)	1.98**	0.2151	(0.4109)	0.1645	(0.3708)	5.57***
Secondary School	0.1775	(0.3821)	0.1000	(0.3002)	5.71***	0.1851	(0.3884)	0.1159	(0.3202)	8.14***
Post Secondary School	0.1289	(0.3351)	0.1022	(0.3031)	2.20**	0.1418	(0.3489)	0.1732	(0.3785)	-3.99***
Graduate	0.0915	(0.2884)	0.0753	(0.2640)	1.56	0.1029	(0.3039)	0.1452	(0.3524)	-6.10***
Training. Reference: No Training										
Vocational	0.0354	(0.1848)	0.0191	(0.1370)	2.50**	0.0130	(0.1134)	0.0118	(0.1081)	0.49
General	0.0261	(0.1595)	0.0270	(0.1621)	-0.14	0.0517	(0.2213)	0.0849	(0.2787)	-6.48***
Marital Status. Reference: Single										
Married	0.7787	(0.4152)	0.6056	(0.4890)	11.05***	0.7539	(0.4308)	0.6220	(0.4850)	13.47***
Divorced	0.0011	(0.0328)	0.0618	(0.2409)	-16.38***	0.0016	(0.0401)	0.0582	(0.2341)	-27.91***
Widowed	0.0032	(0.0568)	0.1416	(0.3488)	-25.31***	0.0056	(0.0745)	0.1461	(0.3533)	-44.05***
Region - Reference: Rural										
Urban	0.5477	(0.4978)	0.7483	(0.4342)	-11.23***	0.4478	(0.4973)	0.6129	(0.4872)	-14.89***
Occupation. Reference: Service										
Professional	0.1427	(0.3498)	0.0674	(0.2509)	6.13***	0.1076	(0.3099)	0.2332	(0.4229)	-17.23***
Administrative	0.0723	(0.2590)	0.1382	(0.3453)	-6.55***	0.0060	(0.0770)	0.0022	(0.0467)	2.28**
Clerical	0.0579	(0.2335)	0.0169	(0.1288)	5.09***	0.0631	(0.2431)	0.0700	(0.2552)	-1.26
Sales	0.0663	(0.2488)	0.2944	(0.4561)	-21.32***	0.0720	(0.2584)	0.0232	(0.1505)	8.81***

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Table 3 (continued): Descriptive Statistics: Sample in Full-Time Employment

	LFS 1999					LFS 2005				
	Male		Female		Difference	Male		Female		Difference
Variable	Mean	Std. Dev.	Mean	Std. Dev.	t-test	Mean	Std. Dev.	Mean	Std. Dev.	t-test
Agriculture	0.3532	(0.4780)	0.1528	(0.3600)	11.88***	0.3160	(0.4649)	0.1325	(0.3392)	18.19***
Production	0.1628	(0.3692)	0.2831	(0.4508)	-8.58***	0.3365	(0.4725)	0.3640	(0.4812)	-2.59***
Industry. Reference: Hospitality										
Agriculture	0.3441	(0.4751)	0.1303	(0.3369)	12.81***	0.3104	(0.4627)	0.1133	(0.3170)	19.72***
Manufacturing	0.2416	(0.4281)	0.3393	(0.4737)	-6.12***	0.2911	(0.4543)	0.3740	(0.4840)	-8.10***
Wholesale and Retail	0.0661	(0.2484)	0.0157	(0.1245)	5.90***	0.0636	(0.2440)	0.0092	(0.0954)	10.54***
Transport	0.0715	(0.2576)	0.0090	(0.0944)	7.14***	0.0816	(0.2737)	0.0131	(0.1138)	11.81***
Financial Institution	0.0240	(0.1530)	0.0090	(0.0944)	2.82***	0.0279	(0.1646)	0.0446	(0.2065)	-4.40***
Real Estate	0.0047	(0.0688)	0.0056	(0.0748)	-0.34	0.0073	(0.0849)	0.0052	(0.0723)	1.08
Public Administration	0.0775	(0.2674)	0.0371	(0.1891)	4.31***	0.0679	(0.2515)	0.0547	(0.2274)	2.37**
Education	0.0468	(0.2113)	0.1045	(0.3061)	-6.87***	0.0707	(0.2563)	0.1767	(0.3815)	-17.26***
Health	0.0130	(0.1131)	0.0315	(0.1747)	-4.04***	0.0190	(0.1365)	0.0626	(0.2422)	-12.68***

$***: p < 0.01; **: p < 0.05; *: p < 0.1$

Table 4: Decomposition of Gender Wage Gap

Quantile	Total Gap	Percentage Gap	Endowment	Discrimination	Proportion Due to Discrimination
1999					
0.10	0.5026	65.30	0.0831	0.4195	0.8347
0.25	0.5423	72.00	0.0194	0.5229	0.9642
0.50	0.4688	59.81	-0.0073	0.4761	1.0156
0.75	0.5551	74.21	0.0033	0.5518	0.9941
0.90	0.2261	25.37	0.0523	0.1738	0.7687
Mean	0.4542	57.49	0.0318	0.4224	0.9300
2005					
0.10	0.7303	107.57	0.1691	0.5612	0.7685
0.25	0.8475	133.38	0.2301	0.6174	0.7285
0.50	0.6530	92.13	0.1324	0.5206	0.7972
0.75	0.4747	60.75	0.0359	0.4388	0.9244
0.90	0.4050	49.93	-0.0173	0.4223	1.0427
Mean	0.6488	91.32	0.1231	0.5257	0.8103

Percentage Gap computed as $(\exp(\text{Total Gap}) - 1) \times 100$
Male Wages is the Reference Category

Table 5: Decomposition of Change in Wage Gap

Quantile	Total Gap	Percentage Gap	Endowment	Discrimination	Proportion Due to Discrimination
0.10	0.2277	25.57	-0.1720	0.3997	1.7554
0.25	0.3052	35.69	-0.209	0.5142	1.6848
0.50	0.1842	20.23	-0.1529	0.3371	1.8301
0.75	-0.0804	-7.73	0.0413	-0.1217	1.5137
0.90	0.1788	19.58	0.1273	0.0515	0.2880
Mean	0.1946	21.48	-0.0973	0.2919	1.5000

Percentage Gap computed as $(\exp(\text{Total Gap}) - 1) \times 100$
2005 Wages is the Reference Category

Table 6: Decomposition of Wage Gap with Selection

Quantile	Observed Wage Gap	Endowment	Discrimination	Selection Effect	Percentage Gap	Proportion Due to Discrimination
1999						
0.10	0.5026	0.0955	0.2461	0.1610	40.72	0.7204
0.25	0.5423	0.0239	0.3977	0.1207	52.44	0.9433
0.50	0.4688	-0.0482	-0.2673	0.7842	-27.05	0.8475
0.75	0.5551	-0.0424	0.1842	0.4133	15.23	1.2990
0.90	0.2261	0.0343	0.0978	0.0940	14.12	0.7403
Mean	0.4542	0.0135	-0.0067	0.4474	0.68	-0.9853
2005						
0.10	0.7303	0.1659	-0.0338	0.5982	14.12	-0.2559
0.25	0.8475	0.2301	0.8270	-0.2096	187.80	0.7823
0.50	0.6530	0.1203	0.0588	0.4739	19.61	0.3283
0.75	0.4747	0.0244	0.1708	0.2795	21.56	0.8750
0.90	0.4050	-0.0308	-0.3493	0.7850	-31.61	0.9192
Mean	0.6488	0.1125	0.3922	0.1441	65.65	0.7771

Percentage Gap computed as (exp(Offered Wage Gap) $-$ 1) $\times$ 100
Male Wages is the Reference Category

Table 7: Decomposition of Change in Wage Gap with Selection

Quantile	Observed Wage Gap	Endowment	Discrimination	Selection Effect	Percentage Gap	Proportion Due to Discrimination
0.10	0.2277	-0.1634	-0.0462	0.4373	-18.91	-0.2199
0.25	0.3052	-0.2124	0.8479	-0.3303	88.80	1.3342
0.50	0.1842	-0.1498	0.6446	-0.3103	63.97	1.3035
0.75	-0.0804	0.0414	0.0121	-0.1339	5.50	0.2262
0.90	0.1788	0.1352	-0.6473	0.6909	-40.08	1.2640
Mean	0.1946	-0.1051	0.6029	-0.3032	64.51	1.2111

Percentage Gap computed as $(\exp(\text{Offered Wage Gap}) - 1) \times 100$
2005 Wages is the Reference Category

Figure 1: Distribution of Log Real Hourly Wages, by Gender

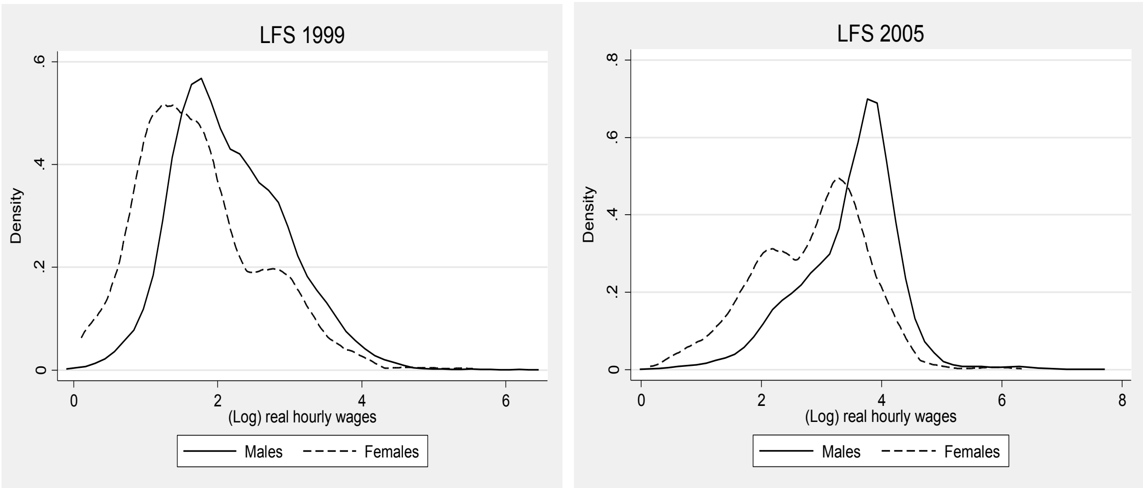

Figure 2: Changes in the Distribution of Log Real Hourly Wages, by Gender

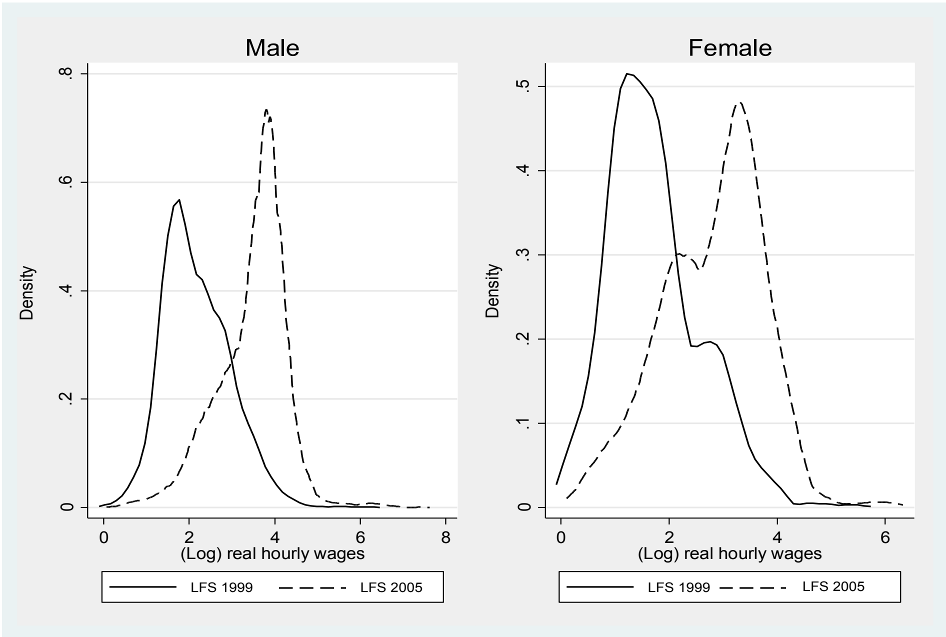

Figure 3: Is there a Selection Effect?

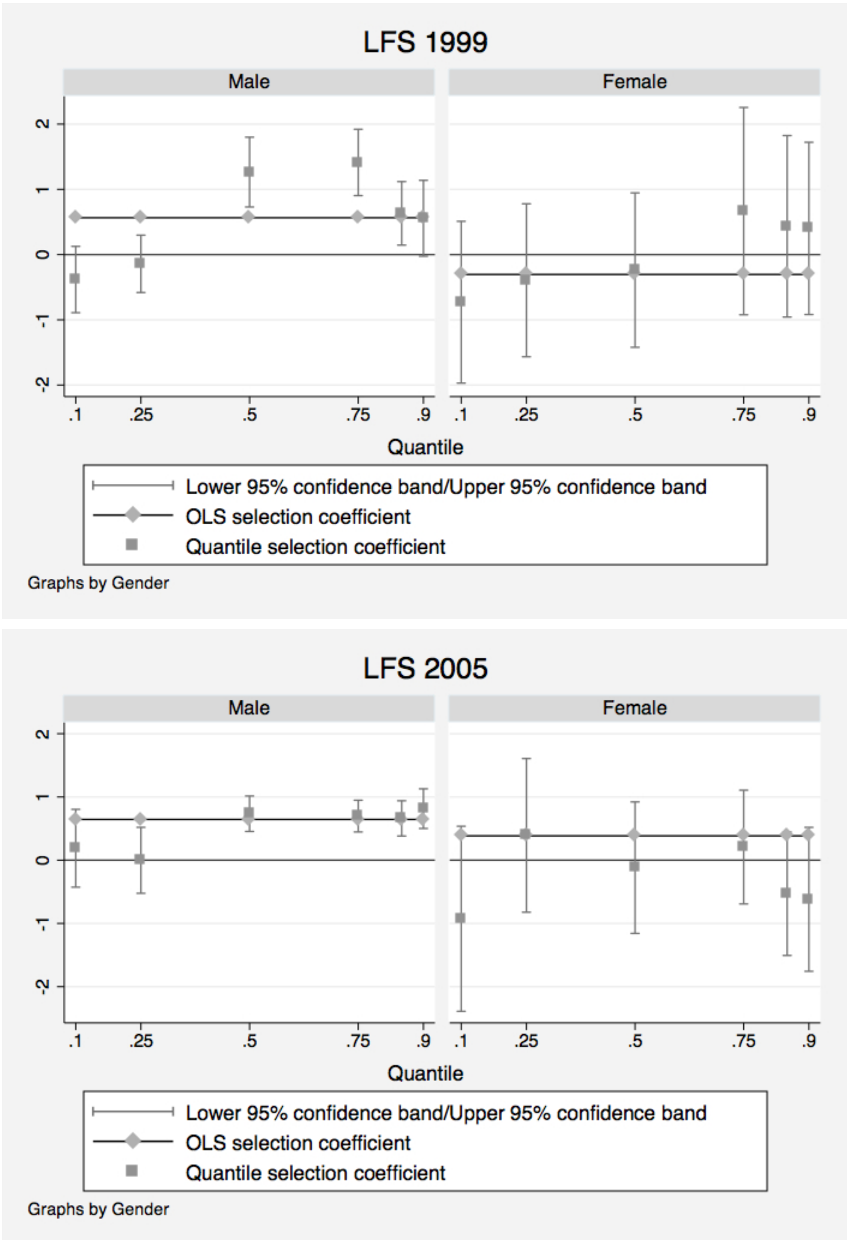

Table A-1: Decomposition of the Gender Wage Gap at Mean and at Different Quantiles

	1999						2005					
	$\nu = 0.10$	$\nu = 0.25$	$\nu = 0.50$	$\nu = 0.75$	$\nu = 0.90$	Mean	$\nu = 0.10$	$\nu = 0.25$	$\nu = 0.50$	$\nu = 0.75$	$\nu = 0.90$	Mean
Panel A: No Selection												
Differences in observed wages	0.5026	0.5423	0.4688	0.5551	0.2261	0.4542	0.7303	0.8475	0.653	0.4747	0.4049	0.6488
Contribution of Characteristics												
Age	0.035	0.0295	0.0427	0.0593	0.0493	0.0425	0.0098	0.0172	0.0035	0.005	0.0049	0.0070
Education	0.0232	0.0263	0.0613	0.0557	-0.0164	0.0295	-0.0414	-0.0494	-0.0069	0.0048	0.0069	-0.0144
Training	0.0011	0.0009	0.0032	0.0058	0.009	0.0042	0.0045	0.009	0.0047	0.0017	0.0013	0.0046
Marital Status	0.0318	0.0431	0.0496	0.0248	0.0087	0.0366	0.0574	0.0068	0.0296	0.0179	-0.0065	0.0275
Urban	0.0203	-0.0282	-0.0553	-0.0457	-0.066	-0.0421	0.008	-0.0005	-0.0023	-0.0068	-0.0068	0.0001
Occupation	0.0113	-0.0009	-0.0404	-0.0625	0.0031	-0.0065	0.0891	0.1318	0.016	-0.0015	-0.025	0.0286
Industry	0.001	-0.0513	-0.0684	-0.034	0.0647	-0.0323	0.0416	0.1151	0.0878	0.0148	0.0079	0.0699
Total	0.0831	0.0194	-0.0073	0.0033	0.0523	0.0318	0.1619	0.2301	0.1324	0.0359	-0.0173	0.1231
	(17%)	(4%)	(-2%)	(0.60%)	(23%)	(7%)	(22%)	(27%)	(20%)	(7.60%)	(-4%)	(19%)
Discrimination	0.4195	0.5229	0.4761	0.5518	0.1738	0.4224	0.5612	0.6174	0.5206	0.4388	0.4223	0.5257
	(83%)	(96%)	(102%)	(99%)	(77%)	(93%)	(77%)	(73%)	(80%)	(92%)	(104%)	(81%)
Panel B: With Selection												
Differences in observed wages	0.5026	0.5423	0.4688	0.5551	0.2261	0.4542	0.7303	0.8475	0.653	0.4747	0.4049	0.6488
Differences in selection bias	0.161	0.1207	0.7842	0.4133	0.094	0.4474	0.5982	-0.2096	0.4739	0.2795	0.785	0.1441
Differences in offered wages	0.3416	0.4216	-0.3155	0.1418	0.1321	0.0068	0.131	1.0571	0.1719	0.1952	-0.3801	0.5047
Contribution of Characteristics												
Age	0.0388	0.0309	0.0303	0.0454	0.0438	0.0336	0.009	0.0172	0.0006	0.0022	0.0017	0.0045
Education	0.0254	0.0271	0.0542	0.0477	-0.0196	0.0540	-0.0435	-0.0494	-0.0153	-0.0032	-0.0025	-0.0218
Training	0.0011	0.0009	0.0031	0.0057	0.009	0.0036	0.0045	0.009	0.0046	0.0016	0.0012	0.0045
Marital Status	0.0316	0.0447	0.0352	0.0087	0.0023	0.0181	0.0575	0.0068	0.0298	0.018	-0.0063	0.0276
Urban	-0.0178	-0.0273	-0.0634	-0.0549	-0.0696	-0.0358	0.0071	-0.0005	-0.006	-0.0103	-0.0109	-0.0031
Occupation	0.0111	-0.001	-0.0398	-0.0333	0.0034	-0.0073	0.0898	0.1318	0.0187	0.0011	-0.022	0.0309
Industry	0.0008	-0.0513	-0.0677	-0.0618	0.065	-0.0200	0.0416	0.1151	0.0879	0.015	0.0081	0.0700
Total	0.0955	0.0239	-0.0482	-0.0424	0.0343	0.0135	0.1659	0.2301	0.1203	0.0244	-0.0308	0.1125
	(28%)	(6%)	(15%)	(-30%)	(26%)	(199%)	(127%)	(22%)	(70%)	(13%)	(-8%)	(22%)
Discrimination	0.2461	0.3977	-0.2673	0.1842	0.0978	-0.0067	-0.0338	0.827	0.0588	0.1708	-0.3493	0.3922
	(72%)	(94%)	(85%)	(130%)	(74%)	(-99%)	(26%)	(78%)	(34%)	(88%)	(-92%)	(78%)

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Table A-1 (continued): Decomposition of the Gender Wage Gap at Mean and at Different Quantiles

	1999						2005					
	$\nu = 0.10$	$\nu = 0.25$	$\nu = 0.50$	$\nu = 0.75$	$\nu = 0.90$	Mean	$\nu = 0.10$	$\nu = 0.25$	$\nu = 0.50$	$\nu = 0.75$	$\nu = 0.90$	Mean

Numbers in parentheses indicate the percentage of each components contribution to the overall wage gap.

The following explanatory variables are included in each group:

Age: Age 15 – 19, Age 20 – 24, Age 25 – 29, Age 30 – 34, Age 35 – 39, Age 40 – 44, Age 45 – 49, Age 50 – 54, and Age 55 – 59.

Education: Primary School, Secondary School, Post Secondary School, Graduate.

Training: Vocational, General.

Marital Status: Married, Divorced, Widowed.

Occupation: Professional, Administrative, Clerical, Sales, Agriculture, Production.

Industry: Agriculture, Manufacturing, Health, Public Administration, Transport, Financial Institution, Real Estate, Wholesale and Retail and Education.