Cognitive, Non-Cognitive Skills and Gender Wage Gaps: Evidence from Linked Employer-Employee Data in Bangladesh

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Abstract

In this paper, we use a first-hand linked employer-employee dataset representing the formal sector of Bangladesh to explain gender wage gaps by the inclusion of measures of cognitive and non-cognitive skills. Our results show that personality traits have little or weak explanatory power in determining mean wages. Where the personality traits do matter, it is mostly for wages of female employees, and in certain parts of the wage distribution. Cognitive skills as measured by reading and numeracy also seem to confer benefits to men and women differently, with returns varying across the wage distribution. As a result, cognitive skills and personality traits reduce the unexplained gender gap, especially for workers in the upper part of the wage distribution. Finally, the findings suggest that employers place greater consideration on observables such as academic background and prior work experience, and may also make assumptions about the existence of sex-specific skills of their workers, which could then widen the within-firm gender wage gap.

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1 Introduction

The existence of gender wage gaps has been a persistent phenomenon in both industrialized and developing countries.[1] These earnings inequalities can be on account of differences in productive attributes between males and females, and discriminatory practices. There now exists a large body of literature that seeks to disentangle and quantify these two components. The proportion of the wage gap that can be attributed to differences in socio-economic and human capital characteristics is referred to as the "explained component" and the residual "unexplained component" is due to differences in returns to these characteristics. The latter represents a combination of unobservable characteristics, characteristics that are potentially observed by the employer (but not by the researcher), and discrimination.

One such "unobserved" attribute that has recently received significant attention in the literature is non-cognitive or personality or psychological traits.[2] Non-cognitive traits refer to qualities such as motivation, self-esteem, inter-personal skills, etc., that have been shown to be a crucial determinant of labour market performance and educational choices, even after controlling for cognitive skills (e.g., Heckman et al., 2006; Lindqvist and Vestman, 2011). Theoretically, personality traits can have both direct and indirect effects on productivity (Borghans et al., 2008). It can affect productivity directly by being considered as part of an individual's set of productive characteristics. Additionally, it can indirectly affect productivity through its effects on occupational choice (Cobb-Clark and Tan, 2011).

In this paper, our objective is to explain gender wage gaps in the formal sector of Bangladesh as a function of gender differences in cognitive and personality traits, over and above the standard variables included in Mincerian wage regressions. The existing evidence documenting the influence of non-cognitive skills on gender wage gaps is based predominantly on developed economies (e.g., Mueller and Plug, 2006; Heineck and Anger, 2010; Osborne Groves, 2005), with considerable variation in the contribution of these traits - in terms of statistical and economic significance - to the wage gaps. On the other hand, the literature on estimating gender wage gaps in developing and transition countries while fairly large (e.g., Appleton et al., 1999; Chi and Li, 2008; Nordman and Roubaud, 2009; Nordman et al., 2011), has not concerned itself - primarily due to data limitations - with cognitive and non-cognitive skills as potential explanations of the gender wage gap. With new data that allow us to identify these skills and traits in a developing country context, our aim is to contribute to this line of research.

Additionally, since our data are collected at the enterprise level and not at the house-

[1]See Weichselbaumer and Winter-Ebmer (2005) for a meta-analysis of this literature.

[2]Bowles et al. (2001a, 2001b) renewed the interest among economists in the relationship between behavioural and personality traits and labour market outcomes.

hold level, we can construct a linked employer-employee data set with rich information about the firm as well as the employees. Household-level data do not allow one to control for firm characteristics that can often have important implications for wages and wage inequality (see Meng, 2004 and references therein).[3] A priori, including firm-specific effects should alter the magnitude of the gender wage gap if (i), the wage gap is correlated, either negatively or positively, with the firms' observed and unobserved characteristics; (ii), the wage gap between males and females is due to gender-based sorting of workers across firms that pay different wages. For instance, this has been documented in the African manufacturing sector (Fafchamps et al., 2006). With linked employer-employee data, we can include firm-specific effects to account for firm-level influences on the gender wage gaps. A caveat remains that employer-employee data are not representative of the population of interest at the country level, but to the extent that the firms' characteristics matter in the wage formation process, inclusion of firm-specific effects yields important advantages in studying wage gaps.

The next section briefly reviews the literature on gender wage gaps and gives an overview of the labour markets in Bangladesh. Section 3 discusses the methodology. Section 4 describes the data. Section 5 presents the summary statistics and results. Section 6 concludes.

2 Review of Related Literature

2.1 Gender Wage Gaps

Most studies examining gender gaps in earnings are based on data from developed countries. There is especially a renewed literature showing that gender wage gaps vary along the wage distribution. Consequently, looking at gender gaps only at the means of men's and women's wages may only reveal part of the prevailing gender inequalities. Albrecht et al. (2003) find for instance that in Sweden in the 1990s, the gender wage gap was increasing at the upper end of the wage distribution, a phenomenon they termed as "glass ceiling" effect. Similarly, Jellal et al. (2008) find that a glass ceiling exists in France. Arulampalam et al. (2007) in a comparative study document a glass ceiling in some European countries while, in some others, they find a "sticky floor" i.e., larger wage gaps at the lower tails of the earnings distribution. Looking at studies using developing country data, Chi and Li (2008) find a sticky floor in urban China during 1987-2004. While Nordman and Wolff (2009a) find evidence supporting a glass ceiling in Morocco, Nordman and Wolff (2009b) find no compelling evidence of a glass ceiling in Mauritius and Madagascar. Carrillo et al. (2014) based on their examination of gender wage gaps in twelve Latin

[3]For instance, Card et al. (2013) attribute the rise in wage inequality in West Germany to widening of the firm-specific wage differences.

American countries find that poorer and more unequal countries exhibit sticky floors whereas richer and less unequal ones are characterized by glass ceilings. For analyses such as these, studies rely on quantile regression based decomposition techniques that decompose the wage gaps into explained and unexplained components at various points of the wage distribution. They use standard predictors of wage such as age, education, marital status, experience, training etc. and in most cases, much of the wage gap remains unexplained.

Recently, there has been an increased interest in studying whether gender wage gaps can exist on account of gender differences in cognitive and non-cognitive skills. A large experimental literature has established that men and women tend to differ in traits such as competitiveness (e.g., Niederle and Vesterlund, 2007), risk aversion (e.g., Croson and Gneezy, 2009) and willingness to negotiate or bargain (e.g., Babcock and Laschever, 2003), factors that have been shown to explain gender gaps in job-entry decisions (Flory et al., 2010) and educational choices (Buser et al., 2012).[4] Additionally, there is also some evidence that personality traits as measured by concepts such as Big Five and Locus of Control[5] differ across genders - with the magnitude and extent being debated - and this could have implications for pay gaps (e.g., Mueller and Plug 2006; Manning and Swaffield 2008). Mueller and Plug (2006) find a significant but small effect: only 3 percent of the gender wage gap is explained by differences in non-cognitive skills (as measured by the Big Five). Fortin (2008) analyzing data on U.S. workers, reports that 8 percent of the gender wage gap is explained by differences in non-cognitive traits such as importance of money/work and importance of people/family. A similar magnitude has been documented for Russia (Semykina and Linz, 2007), while for Germany (Braakman, 2010) the effects are relatively minor. Using Australian data, Cobb-Clark and Tan (2011) find that men's and women's noncognitive skills significantly influence the occupations in which they are employed in many cases although the nature of relationship varies across gender. To our knowledge, such evidence in a developing country context are scarce, if not non-existent. We provide new evidence for a poor country like Bangladesh, where gender inequalities are found to be large and persistent.

2.2 Labour Markets in Bangladesh

The labour force of Bangladesh has witnessed a steady increase from 46.3 million in 2002-03 to 49.5 million in 2005-06 and 56.7 million in 2010. Most of this increase in employment has been on account of the informal sector, which as of 2010, accounts for 87 percent of total employment. Literacy levels are fairly low with approximately 40 percent of the employed population being illiterate.

[4] See Bertrand (2011) for a review of gender differences in preferences.

[5] Locus of Control reflects the individuals' belief about who controls events in their lives: themselves, or external factors such as other people or circumstances.

Gender disparities heavily characterize the Bangladeshi labour market. The proportion of females in the labour force has increased from 26 percent in 2002-03 to 36 percent in 2010. In terms of sectoral representation, 14.5 percent of males are in the formal sector and the remaining 85.5 percent are in the informal sector. For females, 7.7 percent and 92.3 percent are in the formal and informal sectors respectively.[6] The ready-made garment sector has grown rapidly since its inception in 1980 and has been a significant source of increased paid employment of women with 80 percent of factory workers being female (Khatun et al., 2007). Calculations based on surveys by Heath and Mobarak (2014) suggest that about 15 percent of women in the 16-30 age group are engaged in the ready-made garment industry.

In terms of wages, Kapsos (2008) finds that women in non-agricultural sector earn 21 percent less per hour than men. Ahmed and Maitra (2011) conduct a distributional analysis of gender wage gaps in Bangladesh using the Labour Force Surveys of 1999-2000 and 2005-06. They find that wage gaps have increased across the distribution between the two time periods with wage gaps being higher at the lower end of the distribution, thereby suggesting the presence of a sticky floor phenomenon. Further, they find that the coefficients effect (or discrimination component) accounts for majority of the gender wage gaps.

3 Methodology

3.1 Blinder-Oaxaca Decomposition Framework

We first use the Blinder-Oaxaca method to decompose the mean wage gap between males and females into portions attributable to differences in the distribution of endowments (also known as the explained component) and differences in returns to these endowments (also known as the unexplained component) (Blinder, 1973; Oaxaca, 1973). This methodology involves estimating Mincerian wage equations separately for males and females. The decomposition is as follows:

$$\bar{w}^m - \bar{w}^f = (\bar{X}^m - \bar{X}^f)\hat{\beta}^m + \bar{X}^f(\hat{\beta}^m - \hat{\beta}^f) \tag{1}$$

where the left hand side of the equation is the difference in the mean log hourly wages of males and females. $\bar{X}^m$ and $\bar{X}^f$ are average characteristics for males and females respectively and $\hat{\beta}^m$ and $\hat{\beta}^f$ are the coefficient estimates from gender-specific OLS regressions. The first term on the right hand side represents the part of the wage differential due to differences in characteristics and the second term represents differences due to varying

[6] These figures have been taken from the 'Report on Labour Force Survey 2010' published in 2011 by the Bangladesh Bureau of Statistics.

returns to the same characteristics. The second term is the unexplained component and is generally considered to be a reflection of discrimination.

The decomposition of the wage gap into explained and unexplained components is sensitive to the choice of the non-discriminatory structure. If the non-discriminatory wage structure is the one of males, then male coefficients should be used as in equation (1). Conversely, one can use the female coefficients if there is reason to believe that the wage structure of women would prevail in the absence of discrimination. In order to get around this 'index number problem', solutions have been offered that use some combination of the male and female coefficients. Neumark (1988) 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). In this paper, we rely on the general decomposition proposed by Neumark (1988) which can be written as follows:

$$\bar{w}^m - \bar{w}^f = (\bar{X}^m - \bar{X}^f)\beta^* + [(\hat{\beta}^m - \beta^*)\bar{X}^m + (\beta^* - \hat{\beta}^f)\bar{X}^f] \tag{2}$$

Neumark shows that β^* can be estimated using the weighted average of the wage structures of males and females and advocates using the pooled sample. The first term is the gender wage gap attributable to differences in characteristics. The second and the third terms capture the difference between the actual and pooled returns for men and women, respectively.

3.2 Quantile Decomposition Framework

Generalising the traditional Blinder-Oaxaca decomposition that decomposes the wage gap at the mean, Machado and Mata (2005) proposed a decomposition method that involves estimating quantile regressions separately for males and females and then constructing a counterfactual using covariates of one group and returns to those covariates for the other group.

The conditional wage distribution is estimated by quantile regression. The conditional quantile function $Q_\theta(w|X)$ can be expressed using a linear specification for each group as follows:

$$Q_\theta(w_g|X_g) = X_{i,g}^T \beta_{g,\theta} \; for \; each \; \theta \; \in (0,1) \tag{3}$$

where $g = (m, f)$ represents the groups. w denotes the log of hourly wage, X_i represents the set of covariates for each individual i and β_θ are the coefficient vectors that need to be estimated for the different θ^{th} quantiles.

The quantile regression coefficients can be interpreted as the returns to various characteristics at different quantiles of the conditional wage distribution. The assumption is that all quantiles of w, conditional on X, are linear in X. We can then estimate the conditional quantile of w by linear quantile regression for each specific percentile of $\theta \in (0, 1)$. Machado and Mata (2005) estimate the counterfactual unconditional wage distribution using a simulation-based technique.

Melly (2006) proposed an alternative to the simulation-based estimator of Machado and Mata (2005) that is less computationally intensive. Instead of using a random sample with replacement, Melly (2006) integrates the conditional wage distribution over the entire range of covariates to generate the marginal unconditional distribution of log wage. Then, by inverting the unconditional distribution function, the unconditional quantiles of interest can be obtained. This procedure uses all the information contained in the covariates and makes the estimator more efficient. This estimator is also computationally less demanding and faster. Melly (2006) shows that this procedure is numerically identical to the Machado and Mata decomposition method when the number of simulations used in the Machado and Mata procedure goes to infinity.

We construct a counterfactual for females using the characteristics of females and the wage structure for males:

$$CF_{\theta}^{f} = X_{f,i}^{T}\beta_{m,\theta} \tag{4}$$

Using the abovementioned counterfactual, the decomposition of wage gaps of the unconditional quantile function between groups f and m is as follows:

$$\Delta_{\theta} = (Q_{m,\theta} - CF_{\theta}^{f}) + (CF_{\theta}^{f} - Q_{f,\theta}) \tag{5}$$

The first term on the right hand side represents the effect of characteristics (or the quantile endowment effects) and the second the effect of coefficients (or the quantile treatment effects).

4 Data

The Bangladesh Enterprise-based Skills Survey (ESS) for 2012 was sponsored by the World Bank and carried out by a team of the Human Development South Asia Region (Nomura et al., 2013). The World Bank, together with the government of Bangladesh and the development partners, had embarked on a comprehensive assessment of the education sector. The survey aims to determine whether the education system in Bangladesh is responding adequately to the skills demands of firms. The survey contains only formal sector firms.[7] The ESS is a linked employer-employee survey, containing an employer survey as well as an employee survey for a subsample of employees working in the firms surveyed. The survey samples 500 firms active in commerce, education, finance, manu-

[7]This is a shortcoming of the data as the Bangladeshi economy heavily leans towards the informal sector.

facturing and public administration, while the employee survey samples 6981 employees. The employer module consists of a general enterprise profile, including characteristics of the firm and its managers, its recruitment and retention practices, and the workforce training it provides. The employee module contains information on an employee's education background, work experience, and household background information. Further, the employee surveys contain modules to assess cognitive and non-cognitive skills through specific tests. The survey was conducted between November 2012 and January 2013 through face-to-face interviews.

The Business Registry of 2009, collected by the Bangladesh Bureau of Statistics, was used as the sampling frame. The Business Registry contains 100,194 enterprises that have more than 10 employees in Bangladesh. The sampling methodology for the ESS is stratified random sampling, with the strata being economic sector and firm size. The five economic sectors selected for sampling were: commerce (wholesale/retail), education, finance, manufacturing, and public administration. These five sectors occupy 87 percent of formal sector enterprises and 91 percent of formal sector employment.[8] Enterprises were categorized into three sizes: small (10-20 employees), medium (21-70 employees) and large (71 or more employees). The employees to be interviewed were selected by random sampling. A roster of employees was requested and the samples were drawn in the following manner: in a small firm, every third person from the roster was interviewed; in a medium and large firm, every fifth and seventh persons were selected respectively; and if the employment size exceeds 200, every 30th person was interviewed.

For this analysis, since we are interested in within-firm gender wage gaps, we restrict our sample to firms where at least one male and one female employee have been sampled. This leaves us with a sample of 264 firms and 4527 employees.

Cognitive skills were measured through literacy and numeracy tests. The literacy test consists of eight questions, including reading of words and sentences, and understanding short passages, grammar, and English translation. The numeracy test consists of simple mathematical operations (addition, subtraction, multiplication, division, measurement, and functional mathematics, such as cost calculation). Scores are calculated by assigning one point for each item that a respondent answers correctly.

Non-cognitive or personality traits were assessed by administering a battery of 24 questions to interviewees and asking them to rate how they see themselves on a scale going from 'almost always', 'most of the time', 'some of the time', 'almost never' to 'don't know/refuse'. These questions have been taken from the Big Five Inventory that has the following five dimensions: extraversion, agreeableness, conscientiousness, open-

[8] The selection of economic sectors was made purposively. First the economic sectors have relatively large proportion of firms in the formal economic sector as well as large share of employees. Second, the selected economic sectors are considered to have diversity in educational and skills demand.

ness to experience, and neuroticism (see John and Srivastava, 1999 for definitional and measurement issues).

5 Results

5.1 Summary Statistics

We begin with descriptive statistics of firm characteristics listed in Table 1. 71 percent of firms report themselves as being profitable. On average, there are 173 employees per firm of which 26 percent are females. 35 percent of the sample is made up of small firms, while medium and large firms account for 30 percent and 34 percent respectively. 61 percent of top managers in firms have a post-graduate degree. Only a paltry 4 percent of firms have females in top managerial positions. 96 percent of firms maintain either formal or informal accounts and 96 percent of firms are registered with the government. These two factors reflect the high level of formality in the sampling frame of the survey which is based on the Business Registry (see previous section).

In terms of industrial sectors, the largest chunk of firms (32 percent) is engaged in manufacturing. Finance and education make up approximately 21 percent each. Public administration firms constitute 19 percent while commerce makes up the remaining 6 percent. Further, within the manufacturing firms, textiles and wearing apparel are the dominant activities comprising 35 percent and 25 percent respectively while food products make up 20 percent.

Looking at location, 55 percent of firms are based in Dhaka, the capital city. 12 percent are based in Rajshahi while 10 percent are based in Chittagong, the second largest city in Bangladesh.

Coming now to employee characteristics in Table 2, out of 4527 employees, 877 are female, thereby constituting 19 percent of the employee sample. Males are slightly older than females and there is no difference in the proportion of married males and females. Males have 11 years of education, which is 1 year higher than that of females. Males also have greater tenure at the current firm and years of experience prior to joining the current firm. Given these differences in endowments, a higher wage for men is expected. As our data show, the average hourly wage of males is 50 taka while that of females is approximately 47 taka, with the difference being statistically significant. This translates into a wage gap of about 16 percent. Note that while this wage gap may seem modest for Bangladesh where gender-based inequalities are large and fairly persistent, one should bear in mind that self-selection of high ability workers into the formal sector is a priori greater for women than for men. Moreover, since the informal sector is not under consideration here, the wage gap measured here is an under-estimate of the wage gap characterizing the labour market in Bangladesh.

Another factor that could explain the wage gap is differences in occupational status between males and females. While 4 percent of males and 2 percent of females are in managerial roles, the gap in the proportion of professionals is larger with 25 percent of men and 22 percent of women performing such roles. Further, almost 22 percent of women are in elementary occupations (unskilled) while a much smaller proportion of men (13 percent) are in such occupations.

Moving on to reading and numeracy tests - our measure of cognitive skills - men outperform women significantly with the average reading score being 4.82 and numeracy test score being 5.76 (out of a maximum of 8 in each).

5.2 The Mean Gender Wage Gap

We first estimate OLS regressions for the full sample of males and females. The dependent variable is the log of the current hourly wage. We subsequently expand the list of explanatory variables. The first set consists of socio-economic characteristics such as marital status, years of completed education, years of prior experience and years of tenure (with a quadratic profile for the last three variables). We also introduce a dummy variable which is equal to 1 when the worker is a woman and to zero otherwise. In the second set, to measure cognitive skills, we further include standardized scores on the reading and numeracy tests. In the third set, to measure personality traits, we include standardized values of scores on each of the five dimensions: extraversion, agreeableness, conscientiousness, openness to experience, and neuroticism (emotional instability). Next, in each of these regressions, we can pick up the role of unobserved firm heterogeneity by introducing firm dummies in the regression. Finally, dummy variables for occupational status are also added.[9] If the female dummy variable partially picks up these occupational effects, it would lead to an over-estimated gender effect. However, a problem is that occupational assignment may be itself be the result of the employer's practices and not due to differences in productivity or individual choice (Albrecht et al., 2003). Standard errors are clustered at the firm level.

Results are in Table 3. In column 1, we regress the log wage on only the female dummy and obtain a negative coefficient indicating a significant gender wage gap of 16 percent. In column 2, upon adding the socio-economic controls, the female coefficient reduces drastically to 7.7 percent. In column 3, upon adding the standardized scores on cognition tests, the gender wage gap remains unchanged. The reading score is positively associated with higher wages but the numeracy score is not. In column 4, we further add the standardized scores of the personality traits which leads to a marginal decline in the

[9]Results with occupation status variables are reported in the appendix.

female dummy to 7.1 percent. None of the personality traits are statistically significant. In columns 5-7, we augment each of the regressions by adding the firm dummies. The gender coefficient reduces to 5 percent in the most inclusive specification (column 7). An F-test of joint significance of the firm dummy variables shows them to be highly significant. This indicates wages are correlated with firm-specific factors, thereby making it crucial to account for firm-specific effects.

We also estimate OLS regressions using log of starting wages (results are available with the authors upon request). In the specification that includes reading and numeracy test scores and the personality scores, along with education and prior experience, we find that none of cognitive and non-cognitive traits are significant in determining starting wages.[10] This is in line with expectations since employers consider factors that are easily observed, such as educational attainment, when making hiring decisions and personality factors are probably unobservable from the perspective of the employer at that time. Nyhus and Pons (2005) also find a similar result using Dutch data.

These regressions indicate that personality traits do not matter in a significant way in determining current (or starting) wages. Therefore, they seem unable to affect the gender wage gap.

5.3 Quantile Regressions

As can be seen in Figure 1, the magnitude of the gender wage gap varies considerably throughout the wage distribution with the highest raw gaps being observed at the lower percentiles and the smallest gaps at the highest percentiles. This phenomenon is consistent with the 'sticky floor' observed primarily in developing countries. We now estimate quantile regressions to determine how the magnitude of the gender wage gap changes along the wage distribution once we control for socio-economic characteristics, cognitive and personality traits. By pooling the data for males and females in the quantile regression, the assumption is that the returns to endowments are the same at the various quantiles for men and women. With the pooled sample, the gender dummy in the quantile regressions may be interpreted as the effect of gender on log earnings at the various percentiles once we control for differences in endowments between men and women. In Table 4, we estimate pooled quantile regressions for the most inclusive specification, without firm-specific effects.

The coefficient of the female dummy varies across the wage distribution with gaps being higher at the lower end. The gender wage gap is 15 percent at the 10th percentile, declining to 12.6 percent at the 25th percentile and 9.2 percent at the median. It further declines to 4.5 percent at the 75th and 90th percentiles but is not statistically significant.

[10] Personality measures are included in these regressions under the assumption that such traits are fairly well-developed and time-invariant or stable after one reaches mid-twenties.

The reading score is positive and significant at the 25th and 50th percentiles. Among the personality traits, agreeableness is negatively associated with wages at the 10th percentile.

In Table 5, we add the firm-specific effects. In order to conduct fixed effects quantile regressions, we use the method proposed by Canay (2011). This alternative approach assumes that the unobserved heterogeneity terms have a pure location shift effect on the conditional quantiles of the dependent variable. In other words, they are assumed to affect all quantiles in the same way. The gender wage gap could be a result of sorting of workers across firms that pay different wages and firm fixed effects can help us to get at that. We notice that the inclusion of firm-specific effects affects the gender wage gap differently at the lower and upper parts of the wage distribution. While the gender wage gap is now lower at 10th, 25th and 50th percentiles, it is higher and also statistically significant at the 75th percentile. The wage gap at the 90th percentile, while smaller, is not significant. The reading score seems to have a higher correlation at the lower percentiles than higher ones but the reverse is true for numeracy scores. Conscientiousness is now positively associated with wages at the 75th and 90th percentiles. Similarly, agreeableness is positively associated with wages around the 75th conditional quantile, while neuroticism is on the contrary, negatively associated with wages at the first quartile.

In Table 6, we estimate the gender-specific OLS and quantile regressions with firm fixed effects. The reading score is positively associated with male wages at the 25th and 50th percentile but almost everywhere for female wages. On the other hand, the numeracy score is positively correlated with the wages of men at all of the reported quantiles, but it is not significant anywhere for women. While in the pooled quantile regressions in Table 5, we saw that the coefficient on reading and numeracy scores is positive throughout the distribution, Table 6 shows that these results are quite gender-specific. Considering the personality variables, we see that conscientiousness and agreeableness are both rewarded in women, at the middle and upper middle portions (50th and 75th percentiles) of the wage distribution.

5.4 Decomposition Analysis

Table 7 reports results from the Blinder-Oaxaca decomposition that decomposes the mean wage gap into explained and unexplained components. Panel A only includes socio-economic controls for marital status, education, tenure, prior experience; Panel B also includes the standardized test scores for the reading and numeracy tests, and finally in Panel C, the standardized personality scores are also added. In each of the panels, we report results using the male earnings structure; the female earnings structure and the Neumark pooled model. While columns 2 and 3 report the decomposition results without firm fixed effects, columns 4 and 5 include the firm fixed effects.

Without the firm fixed effects, we see that across all the three panels, using the Neumark decomposition, about half of the gap is explained by characteristics with the remaining half being unexplained. However, with the inclusion of firm fixed effects, the unexplained gap reduces significantly, as expected. 36 percent of the wage gap is unexplained with only the socio-economic characteristics, and reduces to 34 percent and further to 31 percent upon successively adding cognitive and personality traits respectively. Hence, controlling for cognitive and non-cognitive skills does reduce the unexplained component by about 5 percentage points. The effect of non-cognitive skills is precisely 3 percent, which conforms to results obtained by Mueller and Plug (2006) using US data.

Next, we move to the quantile decompositions performed at the 10th, 25th, 50th, 75th and 90th percentiles of the distribution. In Tables 8 and 9, we report results using the male coefficients i.e., if females were paid like males, without and with firm fixed effects respectively. Within each of the three panels, it can be seen that the raw wage gap declines as one moves from the 10th percentile to the 90th percentile. Further, the share of coefficients declines as one moves to the upper end of the distribution, thereby supporting the evidence of a sticky floor. This is reflected in the increasing proportion of the wage gap that can be attributed to differences in characteristics as one moves to the higher quantiles. In panel A, the explained proportion of the gap (characteristics) reaches 39 percent at the 25th percentile, and 69 percent at the 75th percentile; in panel C, the respective proportions are 32 and 88. Besides, cognitive skills and personality traits mostly explain the gender wage gaps of workers in the upper part of the wage distribution, which is in line with quantile regression results reported in Table 6. As an illustration, while the characteristics explain 69 percent of the gap around the third quartile of conditional wages in panel A, this share accounts for more than 88 percent in panel C when cognitive and non-cognitive skills are accounted for. In fact, in each of the panels, note that at the 90th percentiles, differences in characteristics across the genders (over)explain the entire wage gap.

5.5 Within-firm Gender Wage Gap

In this section, we look at factors on account of which firms pay males and females differently. For this, we follow Meng (2004) where wage equations for males and females are estimated separately using a fixed effects model as follows:

$$w_{ij}^m = \beta^m X_{ij}^m + \theta_j^m + \epsilon_{ij}^m \tag{6}$$

$$w_{ij}^f = \beta^f X_{ij}^f + \theta_j^f + \epsilon_{ij}^f \tag{7}$$

The firm fixed effects (θ) are retrieved from these regressions and reflect a premium paid by the firm to its employees, since other socio-economic characteristics have already been controlled for in the fixed effects regression models. The difference between the male and female firm fixed effects ($\hat{\theta}^m$ - $\hat{\theta}^f$) is an estimate of the within-firm gender wage gap. In order to conduct this exercise, the sample has to be restricted to those firms that have at least two male and two female observations.[11] This leaves us with a sample of 158 firms and 2030 employees (1578 males and 452 females).

Next, we introduce a host of firm-level characteristics in order to explain this within-firm wage gap and use OLS regressions. The firm level characteristics we include are: industry dummy variables, size of the firm, age of the firm, proportion of female employees, proportion of females in top managerial roles, whether the firm conducts a performance review from time to time, whether the firm is reported profitable, export status, whether the manager is female and whether the manager has completed college and higher levels of education. In addition, employers are asked to state on a scale of 1-10 (with 10 being most important) how important they think it is for employees, both managers/professionals and non-professionals, to have each of the following skills: problem-solving skills, literacy and numeracy skills, motivation and commitment, general job-specific skills, and advanced job-specific skills. We use the responses on each of these because to the extent that employers value certain skills more than others and have some underlying assumptions about the ability of male and female employees, this could affect the wages paid.

In column 1 of Table 10, we report the estimates of the within-firm gender wage gap where the first step regressions do not take occupational status into account. Within-firm wage gaps are smaller in the manufacturing industry as compared to the commerce industry (reference category). A greater proportion of females in the top management level is associated with a smaller wage gap within the firm. Firms where the managers have completed higher education are also characterized by smaller wage gaps. This is coherent if firms with a greater proportion of female top executives have more incentives to apply gender pay equity. Note that this result holds even if we control for occupations in column 2. In addition, firms that value problem-solving skills and advanced job-specific skills more for the professional workforce and literacy skills more for non-professional workers have lower gender wage gaps. On the other hand, firms where managers place greater importance on literacy skills among professional workers and problem-solving skills and advanced job-specific skills among non-professional workers have higher wage gaps. In column 2, upon taking occupational status into account in the first step regressions, the coefficient on the manufacturing industry dummy variable is still negative and significant indicating smaller wage gaps. The positive effect on the within-firm gender wage

[11] If there is only one person of each sex in a firm, the estimated firm effect would be equal to the residual estimated for this person and firm and individual residuals cannot be separated.

gap of high value given to problem-solving skills and advanced job-specific skills among non-professional employees is robust to the inclusion of occupation status. Hence, in the absence of perfect observation of such skills among employees, perhaps employers make the assumption that males are more endowed than females in such skills, which would tend to increase the gender gap in the wage premium.

6 Discussion and Conclusion

In this paper, our objective has been to explain gender wage gaps in the formal sector in Bangladesh by including measures of cognitive and non-cognitive skills as determinants of wages. We believe it makes an important contribution especially when the existing literature on these issues is scarce for developing countries.

Our results show that, for the particular sample at hand, measures of personality seem to have little or weak explanatory power in determining mean wages. Where the personality traits do matter, it is mostly for wages of female employees, and in certain parts of the wage distribution, in particular in its upper part. We do find evidence that reading and numeracy skills matter, especially when we carry out quantile regressions that go beyond the mean of the wage distribution. Further, reading and numeracy skills seem to confer benefits to men and women differently, albeit positive, at different points of the distribution. For instance, the reading score seems to have a higher correlation at the lower percentiles than higher ones but the reverse is true for numeracy scores. Besides, when looking at decompositions, gender differences in both cognitive and non-cognitive skills matter. Including measures of cognitive skills and personality traits reduces the mean unexplained component by about 5 percentage points when firm effects are also accounted for. While this unexplained share remains sizable despite accounting for these factors in the lower part of the wage distribution, cognitive skills and personality traits greatly reduce the unexplained gender gap of workers in the upper part of the wage distribution. Then, quantile decompositions indicate the presence of a sticky floor phenomenon, which is revealed by higher adjusted wage gaps at the lower end of the conditional wage distribution. This result is in contrast to findings obtained with similar matched worker-firm data for African countries (such as Morocco, Mauritius or Madagascar) where the gender wage gaps in the formal sector were sometimes characterized by a glass ceiling effect (Nordman and Wolff, 2009a, 2009b).

Outlook of employers in our sample may offer a potential explanation for our finding of low returns to non-cognitive skills. In the data, employers are asked to rate how important the following criteria are when making hiring decisions on a 1-10 scale (10 being very important): academic performance, work experience, job skills and interview. 68 percent, 57 percent and 50 percent of employers rated academic performance, work experience, job skills respectively between 8 and 10. On the other hand, only 37 percent of employers considered interview to be an important selection criteria. This suggests that employers place greater consideration on observables such as academic performance and prior work experience, rather than on a face-to-face interaction during an interview, which gives them the opportunity to assess certain soft skills of the person such as their assertiveness, agreeableness, communication skills, etc. Our results are also in line with other studies such as Acosta et al. (2014) that find cognitive skills to matter more than non-cognitive skills for determining labour market outcomes (wages and job type) in urban Colombia, and non-cognitive skills are more salient for wages in sub-groups such as women and young workers.

Finally, we also have investigated the determinants of the within-firm gender wage gap. Sector of activity, education of the manager, share of top position females in the firm all seem to be significant determinants of the wage gap observed inside the firm. Besides, in the absence of perfect observation of workers productivity and skills as hypothesized above, employers seem to use signals to set wages. These signals may be based on skills preference and beliefs in the existence of sex-specific skills. How and why such stereotypes persist and cause gender inequality in labour market outcomes in Bangladesh (and more generally in developing countries) would then be worth investigating further.

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Figure 1: Gender Wage Gap

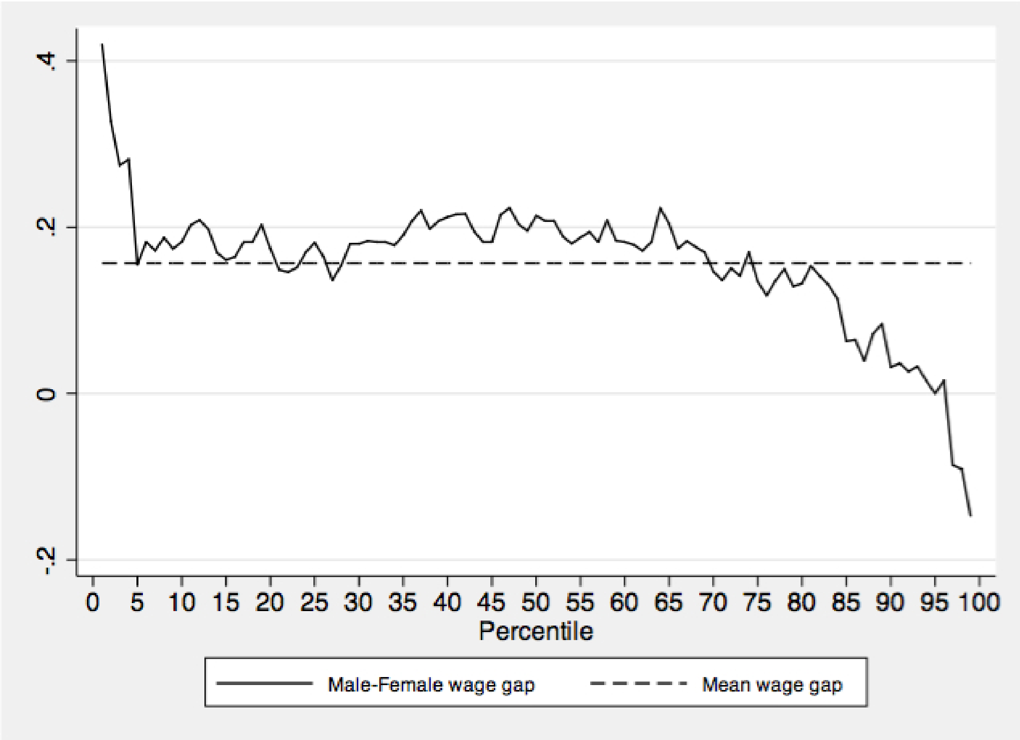

Table 1: Descriptive Statistics of Firm Characteristics

Variable	Mean	SD
Making profit	0.71	0.45
Number of employees	173.21	751.84
Share of female employees	0.26	0.17
Top manager: female	0.05	0.22
Top manager: post-graduate level education	0.61	0.49
Small (10-20 employees)	0.352	0.47
Medium (21-70 employees)	0.303	0.46
Large (71+ employees)	0.344	0.47
Maintain accounts (either formal or informal)	0.966	0.18
Registered with government	0.958	0.2
Industrial sector:		
Commerce	0.057	0.23
Education	0.219	0.41
Finance	0.212	0.41
Manufacturing	0.322	0.47
Public Admn	0.189	0.39
Location:		
Rajshahi	0.112	0.32
Khulna	0.068	0.25
Dhaka	0.549	0.49
Chittagong	0.094	0.29
Barisal	0.049	0.22
Sylhet	0.037	0.19
Rangpur	0.083	0.27
Number of firms	264	

Table 2: Descriptive Statistics of Employee Characteristics

Variable	All	Males	Females
Females	0.19		
	(0.39)		
Hourly wage (in taka)	49.72	50.39	46.92
	(52.83)	(48.53)	(67.83)
Ln(hourly wage)	3.67	3.69	3.53
	(0.63)	(0.61)	(0.69)
Age	31.72	32.01	30.54
	(8.31)	(8.36)	(8)
Married	0.78	0.78	0.78
	(0.41)	(0.41)	(0.41)
Years of education	10.36	10.56	9.54
	(4.89)	(4.74)	(5.38)
Tenure in current firm	5.76	5.9	5.17
	(5.85)	(5.96)	(5.33)
Years of prior experience	1.85	1.94	1.49
	(2.77)	(2.94)	(1.96)
Cognitive Skills:			
Reading test score	4.82	4.93	4.37
	(2.65)	(2.58)	(2.9)
Numeracy test score	5.76	5.84	5.43
	(2.01)	(1.96)	(2.2)
Number of employees	4527		

Note: Standard deviation reported in parentheses. The maximum score in the reading and numeracy tests is 8.

Table 3: OLS regressions

	Col.1	Col.2	Col.3	Col.4	Col.5	Col.6	Col.7
Female	-0.157***	-0.077***	-0.077***	-0.071***	-0.067***	-0.064***	-0.052*
	(0.035)	(0.022)	(0.022)	(0.027)	(0.021)	(0.021)	(0.028)
Married		0.073***	0.075***	0.050*	0.046**	0.048***	0.031
		(0.022)	(0.022)	(0.027)	(0.018)	(0.018)	(0.024)
Years of Education		-0.001	-0.009	0.004	-0.012	-0.028***	-0.019*
		(0.008)	(0.009)	(0.011)	(0.008)	(0.008)	(0.011)
Years of Education squared/100		0.402***	0.417***	0.347***	0.454***	0.489***	0.426***
		(0.040)	(0.042)	(0.048)	(0.039)	(0.040)	(0.051)
Tenure in current firm		0.029***	0.029***	0.033***	0.036***	0.035***	0.038***
		(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Tenure in current firm squared/100		-0.040**	-0.040**	-0.052**	-0.058***	-0.057***	-0.063***
		(0.018)	(0.018)	(0.021)	(0.014)	(0.014)	(0.019)
Prior Experience		0.015	0.015	0.031**	0.018**	0.019**	0.025**
		(0.010)	(0.010)	(0.012)	(0.009)	(0.009)	(0.012)
Prior Experience squared/100		0.033	0.032	-0.017	0.026	0.026	0.018
		(0.049)	(0.049)	(0.052)	(0.042)	(0.042)	(0.050)
Reading Score			0.027*	0.037*		0.048***	0.047***
			(0.016)	(0.019)		(0.014)	(0.018)
Numeracy Score			0.001	-0.010		0.011	0.031*
			(0.015)	(0.018)		(0.014)	(0.017)
Open				0.012			-0.003
				(0.015)			(0.013)
Conscientious				-0.006			0.008
				(0.016)			(0.014)
Extrovert				-0.013			0.002
				(0.018)			(0.022)
Agreeable				-0.007			0.007
				(0.014)			(0.010)
Neurotic				0.010			-0.011
				(0.008)			(0.012)
Constant	3.697***	2.934***	2.990***	2.925***	2.974***	3.085***	3.047***
	(0.026)	(0.055)	(0.066)	(0.076)	(0.047)	(0.051)	(0.067)
Firm fixed effects	No	No	No	No	Yes	Yes	Yes
Occupation controls	No	No	No	No	No	No	No
Observations	4527	4527	4527	2802	4527	4527	2802
R^2	0.010	0.508	0.509	0.501	0.677	0.679	0.672

Note: Dependent variable is log of current hourly wage. Standard errors clustered at the firm level are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 4: Quantile Regressions

	Q10	Q25	Q50	Q75	Q90
Female	-0.148***	-0.126***	-0.092***	-0.045	-0.044
	(0.040)	(0.028)	(0.021)	(0.034)	(0.036)
Married	0.069**	0.079***	0.059***	0.054	0.042
	(0.033)	(0.027)	(0.022)	(0.034)	(0.036)
Years of Education	-0.008	0.001	-0.005	-0.001	-0.002
	(0.017)	(0.010)	(0.008)	(0.009)	(0.010)
Years of Education squared/100	0.368***	0.315***	0.360***	0.369***	0.463***
	(0.063)	(0.044)	(0.033)	(0.042)	(0.049)
Tenure in current firm	0.025***	0.028***	0.032***	0.035***	0.033***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)
Tenure in current firm squared/100	-0.045*	-0.038	-0.053**	-0.043*	-0.039
	(0.025)	(0.026)	(0.024)	(0.022)	(0.025)
Prior Experience	0.005	0.023*	0.032***	0.035***	0.039***
	(0.010)	(0.013)	(0.009)	(0.012)	(0.014)
Prior Experience squared/100	0.053	-0.028	-0.017	-0.006	-0.037
	(0.037)	(0.053)	(0.051)	(0.051)	(0.052)
Reading Score	0.031	0.055***	0.049***	0.029	0.016
	(0.028)	(0.019)	(0.017)	(0.020)	(0.024)
Numeracy Score	0.014	-0.004	-0.008	-0.008	-0.017
	(0.016)	(0.013)	(0.011)	(0.015)	(0.018)
Open	-0.004	0.003	0.007	0.008	0.019
	(0.014)	(0.012)	(0.010)	(0.013)	(0.019)
Conscientious	-0.013	-0.015	-0.011	0.011	0.009
	(0.013)	(0.012)	(0.010)	(0.014)	(0.015)
Extrovert	-0.025	-0.015	-0.020	0.007	-0.019
	(0.028)	(0.024)	(0.022)	(0.024)	(0.013)
Agreeable	-0.035**	-0.001	-0.001	0.001	0.003
	(0.017)	(0.015)	(0.011)	(0.013)	(0.014)
Neurotic	0.015	-0.000	0.002	0.015	-0.002
	(0.015)	(0.018)	(0.013)	(0.015)	(0.029)
Constant	2.593***	2.759***	2.991***	3.155***	3.307***
	(0.105)	(0.066)	(0.055)	(0.057)	(0.061)
Firm fixed effects	No	No	No	No	No
Occupation controls	No	No	No	No	No
Observations	2802	2802	2802	2802	2802

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 5: Quantile Regressions (with firm fixed effects)

	Q10	Q25	Q50	Q75	Q90
Female	-0.102***	-0.099***	-0.059***	-0.052**	-0.014
	(0.030)	(0.024)	(0.017)	(0.021)	(0.025)
Married	0.039	0.032	0.022	0.043**	0.056*
	(0.030)	(0.020)	(0.015)	(0.022)	(0.031)
Years of Education	-0.034***	-0.037***	-0.023***	-0.008	-0.019
	(0.009)	(0.006)	(0.004)	(0.007)	(0.013)
Years of Education squared/100	0.471***	0.489***	0.448***	0.392***	0.469***
	(0.040)	(0.025)	(0.022)	(0.034)	(0.063)
Tenure in current firm	0.039***	0.037***	0.039***	0.034***	0.037***
	(0.006)	(0.003)	(0.004)	(0.005)	(0.006)
Tenure in current firm squared/100	-0.078***	-0.071***	-0.064***	-0.042*	-0.043**
	(0.026)	(0.013)	(0.017)	(0.022)	(0.020)
Prior Experience	0.015	0.013	0.022***	0.026***	0.045***
	(0.016)	(0.010)	(0.007)	(0.008)	(0.013)
Prior Experience squared/100	0.004	0.051	0.018	0.042	-0.030
	(0.075)	(0.048)	(0.042)	(0.035)	(0.044)
Reading Score	0.052***	0.067***	0.047***	0.037***	0.033*
	(0.019)	(0.011)	(0.012)	(0.012)	(0.018)
Numeracy Score	0.026*	0.022**	0.022***	0.031***	0.040**
	(0.013)	(0.011)	(0.008)	(0.012)	(0.017)
Open	-0.017	-0.012	-0.003	0.004	-0.009
	(0.014)	(0.009)	(0.007)	(0.010)	(0.013)
Conscientious	-0.006	0.005	0.006	0.015*	0.028*
	(0.011)	(0.008)	(0.007)	(0.009)	(0.015)
Extrovert	-0.023	-0.017	0.023	0.014	0.031
	(0.014)	(0.015)	(0.022)	(0.020)	(0.026)
Agreeable	0.006	0.006	0.008	0.016*	0.013
	(0.014)	(0.011)	(0.006)	(0.010)	(0.015)
Neurotic	-0.034	-0.030*	-0.010	0.007	0.007
	(0.022)	(0.016)	(0.017)	(0.016)	(0.022)
Constant	2.804***	2.991***	3.062***	3.162***	3.328***
	(0.069)	(0.040)	(0.029)	(0.047)	(0.067)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Occupation controls	No	No	No	No	No
Observations	2802	2802	2802	2802	2802

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 6: Gender-Specific Quantile Regressions (with firm fixed effects)

	OLS Males	OLS Females	Q10 Males	Q10 Females	Q25 Males	Q25 Females	Q50 Males	Q50 Females	Q75 Males	Q75 Females	Q90 Males	Q90 Females
Married	0.047*	0.033	0.065	0.038	0.043*	0.048	0.026	0.032*	0.052**	0.046	0.054	-0.021
	(0.026)	(0.072)	(0.039)	(0.079)	(0.022)	(0.043)	(0.016)	(0.019)	(0.021)	(0.038)	(0.033)	(0.067)
Years of education	-0.018	-0.033	-0.040***	-0.024	-0.038***	-0.038***	-0.023***	-0.033***	-0.004	-0.028*	-0.012	-0.033
	(0.011)	(0.027)	(0.008)	(0.022)	(0.007)	(0.011)	(0.004)	(0.006)	(0.008)	(0.017)	(0.012)	(0.023)
Years of education squared/100	0.422***	0.488***	0.506***	0.455***	0.493***	0.536***	0.442***	0.488***	0.387***	0.447***	0.453***	0.497***
	(0.054)	(0.120)	(0.037)	(0.107)	(0.031)	(0.046)	(0.021)	(0.026)	(0.037)	(0.073)	(0.057)	(0.124)
Tenure in current firm	0.037***	0.048***	0.036***	0.040**	0.040***	0.036***	0.041***	0.047***	0.031***	0.043***	0.033***	0.056***
	(0.006)	(0.017)	(0.006)	(0.020)	(0.004)	(0.007)	(0.004)	(0.005)	(0.006)	(0.011)	(0.008)	(0.017)
Tenure in current firm squared/100	-0.062***	-0.061	-0.067**	-0.024	-0.080***	-0.026	-0.080***	-0.062***	-0.036	-0.050	-0.032	-0.042
	(0.022)	(0.081)	(0.026)	(0.121)	(0.015)	(0.024)	(0.015)	(0.019)	(0.022)	(0.051)	(0.025)	(0.078)
Prior Experience	0.026**	0.025	0.011	0.043	0.010	0.022	0.023***	0.026	0.030***	0.040	0.040***	0.037
	(0.011)	(0.065)	(0.015)	(0.057)	(0.008)	(0.028)	(0.008)	(0.017)	(0.010)	(0.036)	(0.011)	(0.064)
Prior Experience squared/100	0.022	-0.101	0.064	-0.132	0.071**	-0.083	0.047	-0.110	0.014	-0.161	-0.011	-0.174
	(0.044)	(0.202)	(0.071)	(0.528)	(0.036)	(0.336)	(0.045)	(0.142)	(0.038)	(0.402)	(0.042)	(0.840)
Reading Score	0.029	0.088	0.032	0.041	0.058***	0.047*	0.034***	0.088***	0.007	0.084***	0.017	0.095**
	(0.020)	(0.053)	(0.022)	(0.040)	(0.012)	(0.026)	(0.012)	(0.013)	(0.014)	(0.032)	(0.019)	(0.047)
Numeracy Score	0.032	-0.012	0.039***	-0.004	0.030***	-0.020	0.021**	-0.012	0.025**	0.016	0.033**	-0.010
	(0.020)	(0.036)	(0.013)	(0.032)	(0.009)	(0.023)	(0.008)	(0.008)	(0.012)	(0.019)	(0.016)	(0.036)
Open	-0.007	-0.011	-0.032*	0.023	-0.010	-0.009	-0.006	-0.011	-0.001	-0.043**	-0.016	-0.054
	(0.014)	(0.043)	(0.017)	(0.027)	(0.009)	(0.019)	(0.008)	(0.010)	(0.010)	(0.020)	(0.015)	(0.039)
Conscientious	0.000	0.024	0.006	0.009	-0.006	0.028	0.003	0.024***	0.013	0.043*	0.009	0.043
	(0.017)	(0.040)	(0.015)	(0.032)	(0.009)	(0.018)	(0.007)	(0.007)	(0.011)	(0.025)	(0.014)	(0.054)
Extrovert	0.004	-0.012	-0.019	0.052	-0.013	0.006	0.017	-0.011	0.013	-0.039	0.003	-0.062
	(0.019)	(0.036)	(0.018)	(0.138)	(0.018)	(0.117)	(0.018)	(0.025)	(0.018)	(0.124)	(0.029)	(0.140)
Agreeable	0.004	0.039	-0.016	0.016	-0.000	0.004	0.008	0.039***	0.008	0.045**	-0.006	0.045
	(0.011)	(0.032)	(0.016)	(0.032)	(0.011)	(0.016)	(0.008)	(0.009)	(0.010)	(0.020)	(0.014)	(0.029)
Neurotic	-0.002	0.007	-0.029	-0.016	-0.020	0.030	-0.008	0.014	0.023	0.005	0.031	-0.007
	(0.013)	(0.020)	(0.019)	(0.038)	(0.015)	(0.043)	(0.020)	(0.028)	(0.021)	(0.016)	(0.020)	(0.023)
Constant	3.046***	2.999***	2.815***	2.628***	3.003***	2.887***	3.070***	3.001***	3.132***	3.110***	3.294***	3.250***
	(0.070)	(0.173)	(0.068)	(0.158)	(0.040)	(0.087)	(0.029)	(0.045)	(0.044)	(0.117)	(0.069)	(0.131)
Observations	2264	538	2264	538	2264	538	2264	538	2264	538	2264	538

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 7: Mean Wage Decomposition

	Col. 1	Col. 2	Col. 3	Col. 4	Col. 5
		Without firm fixed effects		With firm fixed effects	
Panel A: *Only socio-economic characteristics*	Total difference	Difference in endowments	Difference in coefficients	Difference in endowments	Difference in coefficients
Male non-discriminatory structure	0.157	0.091	0.066	0.143	0.014
Female non-discriminatory structure	0.157	0.075	0.082	0.084	0.073
Pooled (Neumark) non-discriminatory structure	0.157	0.081	0.076	0.101	0.056
% of wage gap (Neumark)	100	51.6	48.4	64.3	35.7
Panel B: *Adding cognitive skills*					
Male non-discriminatory structure	0.157	0.09	0.067	0.144	0.013
Female non-discriminatory structure	0.157	0.076	0.081	0.086	0.071
Pooled (Neumark) non-discriminatory structure	0.157	0.082	0.075	0.104	0.053
% of wage gap (Neumark)	100	52.2	47.8	66.2	33.8
Panel C: *Adding personality scores*					
Male non-discriminatory structure	0.136	0.07	0.066	0.054	0.082
Female non-discriminatory structure	0.136	0.062	0.074	0.083	0.053
Pooled (Neumark) non-discriminatory structure	0.136	0.066	0.07	0.094	0.042
% of wage gap (Neumark)	100	48.5	51.5	69.1	30.9

Note: Panel A includes education, tenure, experience and the squared terms. Panel B further adds standardized scores for cognitive skills. In Panel C, standardized personality scroes are also included.

Table 8: Quantile Decompositions of Log Wage Gaps

Decile	Col.1 Difference	Col.2 Characteristics	Col.3 Coefficients
Panel A: *Only socio-economic characteristics*			
10	0.192 (0.012)	0.063 (0.022)	0.129 (0.022)
25	0.193 (0.01)	0.076 (0.019)	0.117 (0.021)
50	0.171 (0.011)	0.082 (0.022)	0.089 (0.023)
75	0.132 (0.012)	0.091 (0.029)	0.041 (0.03)
90	0.063 (0.017)	0.117 (0.04)	-0.054 (0.038)
Panel B: *Adding cognitive skills*			
10	0.198 (0.013)	0.063 (0.023)	0.135 (0.027)
25	0.194 (0.009)	0.08 (0.018)	0.113 (0.022)
50	0.17 (0.01)	0.085 (0.024)	0.086 (0.023)
75	0.128 (0.012)	0.092 (0.029)	0.036 (0.03)
90	0.069 (0.017)	0.119 (0.039)	-0.049 (0.038)
Panel C: *Adding personality scores*			
10	0.237 (0.019)	0.055 (0.043)	0.182 (0.039)
25	0.199 (0.013)	0.065 (0.027)	0.134 (0.029)
50	0.121 (0.015)	0.054 (0.027)	0.067 (0.031)
75	0.086 (0.015)	0.076 (0.035)	0.01 (0.042)
90	0.039 (0.019)	0.098 (0.05)	-0.059 (0.066)

Note: Bootstrapped standard errors reported in parentheses. Panel A includes education, tenure, experience and the squared terms. Panel B further adds standardized scores for cognitive skills. In Panel C, standardized personality scroes are also included.

Table 9: Quantile Decompositions of Log Wage Gaps (with firm fixed effects)

Decile	Col.1 Difference	Col.2 Characteristics	Col.3 Coefficients
Panel A: *Only socio-economic characteristics*			
10	0.192 (0.011)	0.063 (0.025)	0.129 (0.026)
25	0.193 (0.009)	0.076 (0.019)	0.117 (0.019)
50	0.171 (0.012)	0.082 (0.021)	0.089 (0.021)
75	0.132 (0.015)	0.091 (0.027)	0.041 (0.029)
90	0.063 (0.019)	0.117 (0.045)	-0.054 (0.047)
Panel B: *Adding cognitive skills*			
10	0.198 (0.011)	0.063 (0.025)	0.135 (0.026)
25	0.194 (0.01)	0.08 (0.02)	0.113 (0.02)
50	0.17 (0.012)	0.085 (0.02)	0.086 (0.021)
75	0.128 (0.015)	0.092 (0.026)	0.036 (0.032)
90	0.069 (0.019)	0.119 (0.042)	-0.048 (0.047)
Panel C: *Adding personality scores*			
10	0.237 (0.014)	0.055 (0.032)	0.182 (0.033)
25	0.199 (0.013)	0.064 (0.027)	0.134 (0.032)
50	0.121 (0.016)	0.054 (0.03)	0.067 (0.037)
75	0.086 (0.019)	0.076 (0.037)	0.01 (0.04)
90	0.039 (0.023)	0.098 (0.058)	-0.059 (0.058)

Note: Bootstrapped standard errors reported in parentheses. Panel A includes education, tenure, experience and the squared terms. Panel B further adds standardized scores for cognitive skills. In Panel C, standardized personality scroes are also included.

Table 10: Within-firm gender wage gap

	Col.1	Col.2
Education	-0.229	-0.210
	(0.170)	(0.169)
Finance	-0.227	-0.168
	(0.169)	(0.168)
Manufacturing	-0.346*	-0.335*
	(0.188)	(0.187)
Public Admn	-0.132	-0.142
	(0.167)	(0.165)
Medium size	-0.132	-0.107
	(0.092)	(0.091)
Large size	-0.112	-0.049
	(0.089)	(0.088)
Age of the firm	0.002	0.002
	(0.001)	(0.001)
% Females in total workers	0.257	0.050
	(0.253)	(0.251)
% Females in top management	-0.651**	-0.497**
	(0.250)	(0.248)
Formal performance review	-0.056	-0.075
	(0.066)	(0.065)
Firm is profitable	0.043	0.047
	(0.081)	(0.081)
Exporting	0.115	0.133
	(0.111)	(0.110)
Top manager female	-0.180	-0.109
	(0.133)	(0.132)
Top manager is above college level	-0.208*	-0.113
	(0.109)	(0.108)
How important among professional workers:		
Problem solving skills	-0.061*	-0.041
	(0.034)	(0.033)
Literacy skills	0.054*	0.039
	(0.029)	(0.029)
Numeracy skills	0.030	0.024
	(0.033)	(0.032)
Motivation & committment	0.046	0.049
	(0.031)	(0.030)
General job specific skills	-0.008	-0.013
	(0.027)	(0.026)
Advanced job specific skills	-0.040*	-0.036
	(0.023)	(0.023)
How important among non-professional workers:		
Problem solving skills	0.062**	0.050*
	(0.029)	(0.029)
Literacy skills	-0.058*	-0.039
	(0.030)	(0.030)
Numeracy skills	-0.012	-0.018
	(0.027)	(0.027)
Motivation & committment	-0.031	-0.036
	(0.026)	(0.026)
General job specific skills	-0.016	-0.008
	(0.025)	(0.025)
Advanced job specific skills	0.046**	0.044*
	(0.023)	(0.023)
Constant	0.363	0.240
	(0.278)	(0.275)
Observations	128	128
R^2	0.331	0.263

Note: Dependent variable is the difference of fixed effects $\hat{\theta}^m$ - $\hat{\theta}^f$. *** significant at 1%,** significant at 5%,* significant at 10%.

A Additional Results

Table A.1: OLS regressions (with firm fixed effects and occupation controls)

	Col.1	Col.2	Col.3
Female	-0.055***	-0.052***	-0.042
	(0.020)	(0.019)	(0.026)
Married	0.043**	0.045***	0.023
	(0.017)	(0.017)	(0.023)
Years of Education	-0.014*	-0.029***	-0.023**
	(0.007)	(0.008)	(0.011)
Years of Education squared/100	0.334***	0.368***	0.307***
	(0.041)	(0.042)	(0.054)
Tenure in current firm	0.034***	0.033***	0.036***
	(0.004)	(0.004)	(0.005)
Tenure in current firm squared/100	-0.059***	-0.058***	-0.064***
	(0.013)	(0.013)	(0.018)
Prior Experience	0.014*	0.014*	0.020*
	(0.008)	(0.008)	(0.011)
Prior Experience squared/100	0.035	0.035	0.023
	(0.038)	(0.038)	(0.044)
Reading Score		0.048***	0.050***
		(0.014)	(0.017)
Numeracy Score		0.012	0.028*
		(0.014)	(0.016)
Open			-0.007
			(0.012)
Conscientious			0.008
			(0.014)
Extrovert			0.001
			(0.021)
Agreeable			0.009
			(0.010)
Neurotic			-0.007
			(0.013)
Constant	3.001***	3.116***	3.116***
	(0.043)	(0.051)	(0.071)
Firm fixed effects	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes
Observations	4527	4527	2802
R^2	0.702	0.704	0.701

Note: Dependent variable is log of current hourly wage. Standard errors clustered at the firm level are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table A.2: Quantile Regressions (with firm fixed effects and occupation controls)

	Q10	Q25	Q50	Q75	Q90
Female	-0.120***	-0.071**	-0.070***	-0.024	-0.040
	(0.033)	(0.029)	(0.019)	(0.030)	(0.041)
Married	0.107**	0.095***	0.070***	0.051	0.021
	(0.044)	(0.025)	(0.019)	(0.031)	(0.033)
Years of Education	-0.010	0.004	-0.003	-0.007	0.002
	(0.016)	(0.008)	(0.008)	(0.009)	(0.012)
Years of Education squared/100	0.346***	0.252***	0.310***	0.315***	0.369***
	(0.069)	(0.035)	(0.038)	(0.044)	(0.078)
Tenure in current firm	0.020***	0.029***	0.033***	0.034***	0.033***
	(0.007)	(0.006)	(0.005)	(0.006)	(0.008)
Tenure in current firm squared/100	-0.024	-0.051*	-0.050**	-0.040	-0.039
	(0.022)	(0.027)	(0.024)	(0.027)	(0.029)
Prior Experience	-0.003	0.009	0.021**	0.034***	0.025*
	(0.013)	(0.014)	(0.010)	(0.011)	(0.013)
Prior Experience squared/100	0.089*	0.026	0.022	-0.006	0.008
	(0.053)	(0.056)	(0.055)	(0.059)	(0.049)
Reading Score	0.042	0.054***	0.060***	0.046***	0.025
	(0.028)	(0.016)	(0.013)	(0.017)	(0.023)
Numeracy Score	0.009	-0.001	-0.009	-0.011	-0.027
	(0.016)	(0.015)	(0.009)	(0.013)	(0.019)
Open	-0.006	-0.003	-0.000	0.013	0.017
	(0.015)	(0.010)	(0.011)	(0.013)	(0.017)
Conscientious	-0.009	-0.008	-0.007	0.016	0.007
	(0.013)	(0.009)	(0.011)	(0.012)	(0.020)
Extrovert	-0.024	-0.003	-0.025	-0.017	-0.002
	(0.027)	(0.018)	(0.019)	(0.026)	(0.017)
Agreeable	-0.038**	-0.005	0.005	0.007	0.002
	(0.017)	(0.013)	(0.008)	(0.011)	(0.015)
Neurotic	0.012	0.000	-0.002	0.024	0.000
	(0.019)	(0.010)	(0.015)	(0.015)	(0.025)
Constant	2.953***	3.093***	3.255***	3.607***	3.828***
	(0.134)	(0.086)	(0.078)	(0.093)	(0.159)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Occupation controls	Yes	Yes	Yes	Yes	Yes
Observations	2802	2802	2802	2802	2802

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.