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 only in certain parts of the wage distribution. Cognitive skills as measured by reading and numeracy also seem to confer benefits to women and men respectively, with returns varying across the wage distribution. The decompositions indicate that cognitive skills and personality traits reduce the unexplained gender gap, mainly 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

Non-cognitive skills or personality traits have recently received significant attention as determinants of labour market performance. In fact, these non-cognitive traits, referring to qualities such as motivation, leadership, self-esteem, social skills, etc., have in some cases been shown to be at least as important as cognitive skills for wages and employment prospects (e.g., Heckman et al., 2006; Lindqvist and Vestman, 2011).[1] 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 endowments, or serve as incentive-enhancing preferences (Bowles et al., 2001). Additionally, it can indirectly affect productivity, for instance, through its effects on occupational choice (Cobb-Clark and Tan, 2011) and educational attainment (Heckman et al., 2011).

There is a growing body of literature that has explored gender differences in these personality traits as potential explanations of the gender wage gap.[2] However, the existing evidence is based predominantly on developed economies with considerable variation in the contribution of these traits to the wage gaps. For instance, Mueller and Plug (2006) find that 3 percent of the gender wage gap in U.S. is explained by differences in personality traits (measured by the Big Five). On the other hand, 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 non-cognitive skills significantly influence the occupations in which they are employed although the nature of relationship varies across gender.

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 skills and personality traits, over and above the standard variables included in Mincerian wage regressions.[3] 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

[1] Heckman et al. (2006) show that if an individual moves from the 25th percentile to the 75th percentile in the distribution of non-cognitive skills, wages at age 30 improve by about 10 percent for males, and by more than 30 percent for females. In comparison, a similar movement in the cognitive skill distribution leads to a 20 percent wage increase for males and to 30 percent increase for females.

[2] Further, a large experimental literature has established that men and women tend to differ in behavioural traits such as competitiveness (e.g., Niederle and Vesterlund, 2007), risk aversion (e.g., Croson and Gneezy, 2009) and willingness to negotiate (e.g., Babcock and Laschever, 2003), factors that can partly explain gender differences in job entry (Flory et al., 2014) and wages (Card et al., 2013).

[3] We understand that while non-cognitive skills and personality traits have different connotations, we use them interchangeably. Specifically, "traits" suggest some permanence whereas "skills" suggests that they are malleable and can be learned (Heckman and Kautz, 2012).

(Bangladesh Bureau of Statistics, 2011). Most of this increase has been on account of the ready-made garment sector that has grown rapidly since its inception in 1980, with 80 percent of factory workers being female (Khatun et al., 2007). In terms of wages, Kapsos (2008) finds that women in non-agricultural sector earn 21 percent less per hour than men. To our knowledge, such evidence documenting the influence of non-cognitive skills on gender wage gaps in a developing country context is scarce, if not non-existent. With new data that allow us to identify these skills and traits in a developing country, our aim is to contribute to this line of research.

While the literature on estimating gender wage gaps in developing and transition countries is fairly large (e.g., Appleton et al., 1999; Chi and Li, 2008; Nordman and Roubaud, 2009; Nordman et al., 2011), it has not concerned itself - primarily due to data limitations - with cognitive and non-cognitive skills as determinants of the gender wage gap. Further, since looking at gender gaps at the means of men's and women's wages may only reveal part of the prevailing gender inequalities, we also conduct a distributional analysis of wage gaps. This allows us to analyze how cognitive skills and personality traits are valued at different points of the wage distribution. Quantile regression based decomposition techniques that decompose wage gaps into explained and unexplained components at various points of the wage distribution, have been employed for developed countries where mostly a "glass ceiling effect" is documented, i.e. the gender wage gap is increasing at the upper end of the wage distribution (Albrecht et al., 2003; Jellal et al., 2003). Using matched worker-firm data, similar findings are obtained for developing countries in Africa, such as Morocco, Mauritius or Madagascar (Nordman and Wolff, 2009a, 2009b). On the other hand, in Asian developing countries such as India, China and Bangladesh, larger wage gaps have been observed at the lower tails of the earnings distribution, i.e. the "sticky floor" phenomenon (Khanna, 2012; Chi and Li, 2008; Ahmed and Maitra, 2011).[4]

Additionally, since our data are collected at the enterprise level and not at the household 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). 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 where there is evidence of gender segregation across

[4]Carrillo et al. (2014) based on their examination of gender wage gaps in twelve Latin American countries find that poorer and more unequal countries exhibit sticky floors whereas glass ceilings characterize richer and less unequal ones.

firms (Fafchamps et al., 2009). If there are high paying firms that hire more men than women and if there are at the same time low paying firms hiring more women, then firms' characteristics will influence the gender differences in wages. Controlling for firm heterogeneity should then reduce the magnitude of the gender wage gap. With linked employer-employee data, we can include firm-specific effects to account for such firm-level influences on the gender wage gaps.[5]

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 only in certain parts of the wage distribution. Cognitive skills also seem to confer benefits to women and men respectively, with returns varying across the wage distribution. The decompositions indicate that cognitive skills and personality traits do reduce the unexplained gender gap, mainly for workers in the upper part of the wage distribution. Finally, the within-firm regressions suggest that employers may make assumptions about the existence of sex-specific skills of their workers, which could then widen the within-firm gender wage gap.

The paper is organized as follows: the next section discusses the methodology. Section 3 describes the data. Section 4 presents the summary statistics and results. Finally, Section 5 concludes.

2 Methodology

2.1 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

[5] 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.

to differences in characteristics and the second term represents differences due to varying 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.

2.2 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).

3 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. This is a shortcoming of the data as the Bangladeshi economy heavily leans towards the informal sector. 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, manufacturing 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.[6] 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, both consisting of eight questions. The literacy test includes reading of words and sentences, comprehension of short paragraphs, grammar, and translation from Bangla to English. The numeracy test consists of simple mathematical operations (addition, subtraction, multiplication and division), measurement, and functional mathematics, such as cost calculation.[7] Scores are calculated by assigning one point for each correct answer and then standardized.

Non-cognitive or personality traits were assessed by administering a battery of questions - taken from the World Bank Skills Toward Employment and Productivity (STEP) surveys - to employees and asking them to answer on a 4-point scale ranging from "almost

[6]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.

[7]These questions are potentially measuring "crystallized intelligence" (acquired knowledge) and not "fluid intelligence" (the rate at which people learn) as measured by IQ tests. While these two measures of intelligence are correlated, they measure different facets of cognitive ability.

always", to "almost never" to questions such as "When doing a task, are you very careful?" and "Do you worry a lot?".[8] Of these questions, 15 items measure the following five personality factors or traits, commonly identified as the Big Five: openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism. The Big Five or Five-Factor Model is a broadly accepted taxonomy of personality traits (John and Srivastava, 1999). Openness to experience is the tendency to be open to new aesthetic, cultural, or intellectual experiences. Conscientiousness refers to a tendency to be organized, responsible and hard working. Extroversion relates to an outward orientation rather than being reserved. Agreeableness is related to the tendency to act in a cooperative and unselfish manner. Neuroticism (opposite of emotional stability) is the tendency to experience unpleasant emotions easily, such as anger, anxiety, depression, or vulnerability. Further, two questions were used to measure hostile bias which may be defined as over-attributing hostile intent to peers' behaviours, even when the actual intent is benign or the situation is ambiguous (Dodge, 2003). Finally, four questions adapted from the Melbourne Decision-Making Scale (Mann et al., 1997) were used to assess decision-making. Two of the decision-making items gauged information processing that involves consideration of multiple options when making decisions. The other two items tap assessed the extent to which individuals think about the future consequences of their decisions on themselves and others. Traits are measured by taking the average (standardized) score on items corresponding to each trait. It should be noted that since wages and personality traits are measured contemporaneously in the survey, our results should not be interpreted in a causal manner.[9]

4 Results

4.1 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 (10-20 employees), while medium (21-70 employees) and large firms (71 or more employees) account for 30 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

[8] These questions are available in the appendix.

[9] In fact, Almlund et al. (2011) discuss that addressing the potential problem of reverse causality by using previously measured traits as predictors of later outcomes can lead to an errors in variables problem if the traits evolve over time.

(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 represents 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.

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.

Moving on to employee characteristics in Table 2, out of 4,527 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 on average 11 years of education, which is 1 year higher than that of females. Males also exhibit greater tenure at the current firm and years of experience prior to joining the current firm. Given these differences in endowments, a priori a higher wage for men is expected. As our data show, the average hourly wage of males is 50 taka (0.51 euros in 2014) 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 our sample is comprised of firms in the formal sector with at least 10 employees, and self-selection of high ability workers into the formal sector is a priori greater for women than for men (Kingdon, 1998).[10] Moreover, since the informal sector is not under consideration here, the wage gap measured here is an under-estimate of the actual income 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 significant 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).

Finally, in terms of personality traits, females report significantly higher scores on openness (Wilcoxon rank-sum test; p-value=0.003) and significantly lower scores on

[10] However, using national level household survey data for Bangladesh, Asadullah (2006) find no evidence of significant sample selection into paid employment for both sexes.

decision-making (Wilcoxon rank-sum test; p-value=0.021) as compared to men. Note that females score higher than men in most other personality scores, although the differences fail to reach significance.

4.2 The Mean Gender Wage Gap

We first estimate OLS regressions for the pooled 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). Quadratic effects of experience and tenure are used to approximate the concave profile between these variables and wages. We also introduce a dummy variable that is equal to 1 when the worker is a woman and 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 Big Five traits (extroversion, agreeableness, conscientiousness, openness to experience, and emotional stability), and the scores of hostile bias and decision-making. 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 to account for the fact that wages within the same firm could differ on account of different occupations.[11] 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 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 raw gender wage gap of 15.7 percent. In column 2, upon adding the socio-economic controls, the female coefficient reduces considerably to 7.7 percent. In column 3, once the standardized scores on cognition tests are added, the gender wage gap remains unchanged. The reading score is positively linked with wages but the numeracy score is not. While for rural China, Glewwe et al. (2013) find that reading skills are not significant for determining wages when controlling for educational attainment, in our case we find reading proficiency to have incremental explanatory power. In column 4, we further add the standardized scores of the personality traits, which lead to a decline in the female dummy to 5.5 percent. None of the personality traits are statistically significant suggesting that there is no incremental direct effect of these traits on wages. However, the coefficient of the reading

[11] Results are available upon request.

score variable almost doubles in magnitude in column 4 as compared to column 3. This is indicative of possible indirect effects of personality traits on wages through their positive associations with literacy scores. This is consistent with Borghans et al. (2011) who find that personality traits affect achievement test scores and grades. In columns 5-7, we augment each of these regressions by adding the firm dummies. The gender dummy coefficients are smaller in magnitude, as compared to columns 2-4. In the most inclusive specification in column 7, the gender coefficient reduces to 3.3 percent and is no longer significant, suggesting the existence of sorting of male and female workers across firms that pay different wages. 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. In terms of other independent variables included in Table 3, we find that the education-wage relationship follows a convex profile. While this is contrary to the standard assumption of concave relationship between education and earnings, there is now ample evidence suggesting increasing returns to education across schooling levels (e.g., Kingdon and Unni, 2001; Söderbom et al., 2006). Tenure in current firm has the expected concave relationship with wages.[12]

These regressions indicate that while cognitive skills as measured by reading scores directly affect wages, personality traits do not matter in a direct manner on pooled mean wages across the sexes. We then proceed to checking for the existence of specific gender and distributional effects.

4.3 Quantile Regressions

As can be seen in Figure 1, the magnitude of the unconditional gender wage gap varies considerably throughout the wage distribution with the highest gaps being observed at the lower percentiles and the smallest wage gaps at the highest percentiles. This phenomenon is consistent with the "sticky floor" parabola that has been 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 skills, 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. We will relax

[12]We also estimated OLS and quantile regressions using log of starting wages (results available upon request). Personality measures are included in these regressions under the assumption that such traits are fairly well-developed and stable after one reaches mid-twenties. In the specification that includes scores of cognitive skills and personality traits, along with socio-economic characteristics, we find that none of non-cognitive traits are significant in determining starting wages. This is in line with expectations since employers consider factors that are easily observed, such as educational qualifications, 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.

this assumption later on. 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 11 percent at the 10th percentile, and 14.1 percent at the 25th percentile and then declining to 8.7 percent at the median. It further declines to 4.9 percent at the 75th and becomes negligible and insignificant at the 90th percentiles. The reading score is positive and significant at all percentiles except the 90th. Among the personality traits, openness to experience and decision-making are 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. We notice that with the inclusion of firm-specific effects, the gender wage gap is lower at all the estimated percentiles of the wage distribution, as compared to results of Table 5. There is then evidence of sorting across firms by workers at all points of the wage distribution. The wage gap at the 90th percentile, while reversed and now in favor of women is not significant. The reading score seems to have a higher correlation with wages at the lower percentiles than higher ones but the opposite is mostly true for numeracy scores. Agreeableness is positively associated with wages at the 10th, 25th and 50th percentiles, and emotional stability is positively associated with wages at the first decile. On the contrary, openness to experience is negatively associated with wages at the 10th percentile. Conscientiousness is differentially related with wages at both ends of the conditional distribution: negatively linked with wages at the 10th percentile, but positively related to wages at the 90th percentile. Hence, while we do not observe significant effects of non-cognitive skills on mean wages, the observed effects are more nuanced when one looks across the conditional wage distribution.

In Table 6, we estimate the gender-specific OLS and quantile regressions with firm-specific effects.[13] The reading score is positively associated with male wages at only the 25th and 50th percentiles but everywhere with female wages. On the other hand, the numeracy score is positively correlated with the wages of men at all points except the 90th percentile, but is never significant for women. While in the pooled quantile regressions with firm-specific effects in Table 6, we saw that the coefficients on reading and numeracy scores are positive throughout the distribution, it is now evident that these results are differentiated by gender. Considering the personality variables, we observe that conscientiousness is rewarded for women at all percentiles except the 90th but never

[13]To save space, we do not report the gender-specific regressions without firm fixed effects (available upon request).

for men. Agreeableness also has positive and increasing returns for women across the conditional wage distribution. This is in line with Mueller and Plug (2006) who also find agreeableness and conscientiousness to be more rewarding for women. On the other hand, openness has increasingly negative returns for women at the 50th, 75th and 90th percentiles. Interestingly, we find that emotional stability is negatively related with women's wages at the median and the third quartile, although weakly. On the contrary, for men, the effects of personality traits are more sporadic and reveal no consistent pattern, indicating that these personality traits are important determinants for women's wages but not for men's wages. Our results of gender-specific quantile regressions provide some support about the market rewarding individuals who adhere to societal expectations about gender-appropriate traits and behaviour. For instance, agreeableness is a positive quality associated mostly with women especially in a developing country context, and in our sample, we find that agreeable women are rewarded monetarily for this trait. Further, the result that numeracy is a skill rewarded for men and literacy a skill rewarded for women, also bolsters the argument of gendered cultural expectations, particularly in a gender-unequal society such as Bangladesh. Guiso et al. (2008) show that the gender gap in mathematics scores is higher in more gender-unequal societies and it becomes smaller in more gender-equal cultures. On the other hand, the reading score gap is usually in favour of women and becomes smaller in more gender-equal cultures. This could possibly lead to employers forming beliefs about comparative advantages that men and women have in numeracy and literacy skills respectively and adhering to those stereotypes.

4.4 Decomposition Analysis

Table 7 reports results from the mean decomposition that decomposes the average 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 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 wage structure, the female wage structure, and the Neumark pooled model. While columns 2 and 3 report the decomposition results without firm-specific effects, columns 4 and 5 include the firm-specific effects.

Without the firm-specific effects, we see that across all the three panels, using the Neumark decomposition, a little over half of the gap is explained by characteristics with the rest being unexplained. As we move down from panel A to panel C, the unexplained component reduces by 2 percentage points from 48 percent to 46 percent. However, with the inclusion of firm-specific effects, the unexplained gap reduces significantly within each of the panels, as expected. Looking across panels, 35.5 percent of the wage gap is unexplained with only the socio-economic characteristics, and reduces to 34 percent

and further to 22 percent upon successively adding cognitive and personality traits respectively. Hence, in the presence of firm-specific effects, controlling for cognitive and non-cognitive skills reduces the unexplained component by about 13.7 percentage points. To the extent that the unexplained component is indicative of gender wage discrimination, controlling for previously unmeasured cognitive and non-cognitive skills gets us to a closer approximation of labour market discrimination. The effect of non-cognitive skills is precisely 12.1 percentage points.

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-specific 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 of Table 9, the characteristics account for 46 percent (0.081/0.176) of the wage gap at the 25th percentile, and 79 percent (0.089/0.113) at the 75th percentile; in panel C, the respective proportions are 25 and 139 percent. Besides, personality traits mostly explain the gender wage gaps in the upper part of the conditional wage distribution as illustrated by the drastic increase in the explained component at the 75th and 90th percentiles, as one moves from panel B to panel C. In fact, in each of the panels, note that at the 90th percentiles, differences in characteristics between the sexes (over)explain the entire wage gap.

In a nutshell, the decompositions highlight that, contrary to what gender-pooled regressions on mean wages predict, the effects of cognitive and non-cognitive skills are essentially gender specific, and are thereby able to explain a non-negligible proportion (12 percent) of the gender wage gap. Besides, looking at distributional effects, personality traits appear to reduce the unexplained gender gap in the upper part of the conditional wage distribution.

4.5 The Determinants of the Within-firm Gender Wage Gap

In this section, we look at factors on account of which firms pay males and females differently. In relation to the previous sections, the purpose of this analysis is to identify how employers' valuation of employees' cognitive and non-cognitive skills may affect the magnitude of the within-firm gender wage gap. Indeed, to the extent that employers value certain skills more than others, and have some underlying assumptions (i.e. common beliefs or stereotypes) about the ability of male and female employees in the absence of perfect information on their productivity, this could affect the premium they pay to the

two groups of employees. Hence, the difference in firm fixed effects may capture the way in which employers reward cognitive and non-cognitive skills differently across gender. For this, we follow a hierarchical modelling approach (Bryk and Raudenbush, 1992), also applied in Meng (2004) and Nordman and Wolff (2009a), where wage equations for males and females are first estimated separately using a fixed effects model:

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

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

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 (marital status, years of education, prior work experience, and tenure at current firm) have already been controlled for in the fixed effects regression models.[14] 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.[15] This leaves us with a sample of 164 firms and 3231 employees (2494 males and 737 females).

In a second step, 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 consider are: economic sector dummy variables, size of the firm, whether the firm is reported profitable, export status[16], age of the firm, proportion of female employees in the overall firm manpower, proportion of females in top managerial roles, whether the firm conducts a performance review from time to time[17], and whether the manager is female and whether the manager has completed college and higher levels of education.

Employers are also 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: communication, team work, problem-solving, literacy and numeracy, customer care, responsibility, reliability and trustworthiness, creativity, and vocational job-specific skills. We use the responses on each of these by computing standardized scores. In addition, employers are asked to list the top 3

[14] Our results are robust to controlling for occupations in the first stage regressions.

[15] 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.

[16] A large literature in economic theory suggests that a firm's industrial affiliation, profitability, size and openness to international trade should all affect its compensation policy.

[17] Some studies indicate that firms with less information about individuals' productivity may pay one group of workers (males) more than the other group (females), the latter conveying potentially less reliable information about its productivity (Lundberg and Startz, 1983). Hence, the gender wage gap may result from a lack of information. To control for this, it is then useful to identify firms for which individual productivity can be measured. We proxy this with a dummy taking value one if the firm conducts a performance review from time to time.

cognitive and non-cognitive skills (among 14 skills in the questionnaire) they use to make decisions regarding compensation and promotions, separately for managers/professionals and non-professionals.[18] We then construct dummy variables for professionals and non-professionals respectively taking the value 1 if employers declared any non-cognitive skills to be either first or second most important, as compared to cognitive skills.

In column 1 of Table 10, we report the estimates of the within-firm gender wage gap including a set of firm characteristics and two dummies for value given by employers to non-cognitive skills for compensation and promotion for professionals and non-professionals respectively. Looking at the dummy indicating that employers value non-cognitive skills for compensation and promotion, the effect is positive and significant for non-professionals only. This means that, all else being equal, employers who rely on non-cognitive skills, as opposed to cognitive skills, to set their wage policy and to decide on promotions of non-professionals are also those who discriminate the most against women. This might be due the fact that they use these non-cognitive skills as signals in the absence of better information on cognitive credentials, in particular for women.

In columns 2 and 3, we replace the dummies for overall value given to non-cognitive skills by standardized scores of importance given by employers to each of these skills, for non-professionals (column 2) and for professionals (column 3) to save on degrees of freedom. While none of the effects are significant for professionals, we obtain that firms that value problem-solving skills for non-professional workers have significantly greater gender wage gaps. This effect is robust when one considers a regression including all the regressors for professionals and non-professionals (column 4). Finally, in this most inclusive specification of column 4, valuing communication skills among non-professional workers appears to be negatively associated with the within-firm gender wage gap. 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 certain skills (such as problem solving), which would tend to increase the gender gap in the wage premium. In the same way, a supposed typical female trait like communication skills tends to decrease such a gap.

In terms of other firm characteristics, the share of females in the top management and the top manager being female is associated with smaller wage gaps within firms. This effect is robust across all specifications reported. Gender wage gaps tend to be smaller in the education sector as compared to commerce (reference category) and this holds true across columns 1-3. Other variables such as education level of the manager, size of the firm and proportion of females in the overall workforce are not consistently significant in

[18]The set of cognitive skills are: problem solving, literacy, numeracy, ICT, general vocational job-specific skills, advanced vocational job-specific skills and English language, while the non-cognitive skills include communication, team work, customer care, responsibility, reliability and trustworthiness, motivation and commitment, creativity, and confidence.

explaining within-firm gender wage gaps.

5 Discussion and Conclusion

In this paper, our objective has been to explain gender wage gaps in the formal sector of 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, while cognitive skills are positively correlated with wages, measures of personality seem to have almost no explanatory power in determining mean wages for the full sample of males and females. Where the personality traits do matter, it is mostly for wages of female employees, and in certain parts of the wage distribution. Interestingly, the finding that reading and numeracy skills are positively correlated with wages across the distribution are driven by employees' sex such that reading and numeracy skills seem to confer benefits to men and women respectively. 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 14 percentage points when firm effects are also accounted for. Quantile decompositions also 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, with unexplained component being larger at lower percentiles. Personality traits greatly reduce the unexplained gender gap in the upper part of the conditional wage distribution.

Outlook of employers in our sample may offer a potential explanation for our finding of cognitive skills and socio-economic characteristics being more important than non-cognitive skills in determining wages. In the data, employers are asked to rate how important the following criteria are on a 1-10 scale when making hiring decisions (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 36 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. These results are in contrast to studies based on developed countries such as the United States that find employers rank "attitude" as most important skill among new hires (Bowles et al., 2001). Our results are however, in line with other developing country studies such as Glewwe et al. (2013)

that find only suggestive evidence that non-cognitive skills matter for wage determination in rural China, after conditioning on years of schooling, work experience and cognitive skills.

Finally, we also have investigated the determinants of the within-firm gender wage gap. Share of top position females in the firm and sex of the manager all seem to be robust 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 appear to rely on signals to set wages. These signals may be based on skill preference and beliefs in the existence of sex-specific skills. For instance, employers seem to better remunerate those workers making proof of typical perceived 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 be worth investigating further.

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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)
Personality Traits:			
Openness	2.56	2.55	2.62
	(0.59)	(0.59)	(0.59)
Conscientiousness	2.97	2.97	2.96
	(0.59)	(0.59)	(0.62)
Extroversion	2.32	2.32	2.33
	(0.49)	(0.49)	(0.48)
Agreeableness	2.51	2.50	2.54
	(0.61)	(0.60)	(0.61)
Emotional Stability	2.80	2.81	2.77
	(0.56)	(0.56)	(0.56)
Hostile Bias	2.34	2.33	2.37
	(0.73)	(0.72)	(0.75)
Decision-making	2.54	2.58	2.53
	(0.54)	(0.54)	(0.54)
Number of employees	4527		

Note: Standard deviation reported in parentheses. The maximum score for the reading and numeracy tests is 8. The maximum score for the personality traits is 4.

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***	-0.055*	-0.067***	-0.064***	-0.033
	(0.035)	(0.022)	(0.022)	(0.028)	(0.021)	(0.021)	(0.028)
Married		0.073***	0.075***	0.052*	0.046**	0.048***	0.031
		(0.022)	(0.022)	(0.029)	(0.018)	(0.018)	(0.028)
Years of Education		-0.001	-0.009	-0.000	-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***	0.353***	0.454***	0.489***	0.417***
		(0.040)	(0.042)	(0.051)	(0.039)	(0.040)	(0.053)
Tenure in current firm		0.029***	0.029***	0.032***	0.036***	0.035***	0.039***
		(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.005)
Tenure in current firm squared/100		-0.040**	-0.040**	-0.050**	-0.058***	-0.057***	-0.069***
		(0.018)	(0.018)	(0.023)	(0.014)	(0.014)	(0.021)
Prior Experience		0.015	0.015	0.017	0.018**	0.019**	0.014
		(0.010)	(0.010)	(0.016)	(0.009)	(0.009)	(0.015)
Prior Experience squared/100		0.033	0.032	0.049	0.026	0.026	0.073
		(0.049)	(0.049)	(0.074)	(0.042)	(0.042)	(0.068)
Reading Score			0.027*	0.050**		0.048***	0.053**
			(0.016)	(0.021)		(0.014)	(0.021)
Numeracy Score			0.001	-0.012		0.011	0.039*
			(0.015)	(0.020)		(0.014)	(0.020)
Openness				0.002			-0.003
				(0.015)			(0.014)
Conscientiousness				0.004			-0.004
				(0.013)			(0.014)
Extroversion				0.005			-0.009
				(0.013)			(0.012)
Agreeableness				0.006			0.018
				(0.017)			(0.013)
Emotional Stability				0.005			0.007
				(0.013)			(0.011)
Hostile Bias				-0.000			0.003
				(0.012)			(0.012)
Decision Making				-0.024			-0.005
				(0.015)			(0.013)
Constant	3.697***	2.934***	2.990***	2.995***	2.974***	3.085***	3.086***
	(0.026)	(0.055)	(0.066)	(0.080)	(0.047)	(0.051)	(0.063)
Observations	4527	4527	4527	2150	4527	4527	2150
R^2	0.010	0.508	0.509	0.491	0.677	0.679	0.666

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	-0.111***	-0.141***	-0.087***	-0.049	-0.007
	(0.038)	(0.040)	(0.027)	(0.031)	(0.048)
Married	0.109***	0.099***	0.057**	0.049	0.028
	(0.037)	(0.035)	(0.025)	(0.037)	(0.041)
Years of Education	-0.017	-0.010	-0.011	-0.008	0.007
	(0.015)	(0.013)	(0.009)	(0.010)	(0.015)
Years of Education squared/100	0.390***	0.361***	0.380***	0.397***	0.418***
	(0.054)	(0.052)	(0.038)	(0.050)	(0.078)
Tenure in current firm	0.011	0.030***	0.032***	0.036***	0.041***
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)
Tenure in current firm squared/100	-0.005	-0.063**	-0.053*	-0.044	-0.069**
	(0.028)	(0.029)	(0.027)	(0.031)	(0.028)
Prior Experience	-0.001	0.009	0.030**	0.028*	0.014
	(0.013)	(0.014)	(0.013)	(0.014)	(0.018)
Prior Experience squared/100	0.061	0.033	-0.013	0.007	0.151
	(0.048)	(0.063)	(0.071)	(0.083)	(0.101)
Reading Score	0.060**	0.055***	0.056***	0.067***	0.030
	(0.030)	(0.020)	(0.018)	(0.020)	(0.025)
Numeracy Score	0.014	0.000	-0.010	-0.028	-0.038
	(0.020)	(0.015)	(0.011)	(0.019)	(0.026)
Openness	-0.034*	-0.007	0.003	0.011	0.005
	(0.019)	(0.013)	(0.011)	(0.017)	(0.017)
Conscientiousness	-0.001	-0.014	0.003	0.016	0.021
	(0.018)	(0.013)	(0.012)	(0.014)	(0.019)
Extroversion	-0.005	0.016	0.006	0.017	0.000
	(0.015)	(0.012)	(0.009)	(0.013)	(0.014)
Agreeableness	0.014	0.019	0.004	-0.011	-0.000
	(0.021)	(0.014)	(0.011)	(0.015)	(0.015)
Emotional Stability	0.023	0.013	-0.006	-0.006	0.006
	(0.020)	(0.012)	(0.012)	(0.015)	(0.016)
Hostile Bias	-0.001	0.003	0.003	0.006	0.002
	(0.017)	(0.013)	(0.009)	(0.015)	(0.019)
Decision Making	-0.031*	-0.014	-0.017	-0.012	-0.026
	(0.017)	(0.015)	(0.012)	(0.016)	(0.017)
Constant	2.720***	2.834***	3.041***	3.209***	3.294***
	(0.096)	(0.085)	(0.062)	(0.062)	(0.081)
Observations	2150	2150	2150	2150	2150

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors based on 100 replications are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 5: Quantile Regressions (with firm specific effects)

	Q10	Q25	Q50	Q75	Q90
Female	-0.075***	-0.073***	-0.045**	-0.042*	0.009
	(0.027)	(0.023)	(0.019)	(0.023)	(0.036)
Married	0.047*	0.025	0.044***	0.046**	0.035
	(0.027)	(0.021)	(0.016)	(0.023)	(0.035)
Years of Education	-0.034***	-0.037***	-0.022***	-0.007	-0.011
	(0.011)	(0.007)	(0.005)	(0.008)	(0.009)
Years of Education squared/100	0.458***	0.489***	0.428***	0.381***	0.423***
	(0.050)	(0.030)	(0.023)	(0.038)	(0.052)
Tenure in current firm	0.037***	0.041***	0.041***	0.037***	0.037***
	(0.008)	(0.003)	(0.005)	(0.005)	(0.006)
Tenure in current firm squared/100	-0.074**	-0.077***	-0.075***	-0.052**	-0.044**
	(0.031)	(0.012)	(0.019)	(0.021)	(0.019)
Prior Experience	0.011	0.011	0.008	0.016	0.021
	(0.016)	(0.010)	(0.008)	(0.012)	(0.015)
Prior Experience squared/100	0.029	0.055	0.072	0.080	0.112
	(0.080)	(0.048)	(0.050)	(0.065)	(0.078)
Reading Score	0.070***	0.071***	0.055***	0.036***	0.033*
	(0.018)	(0.015)	(0.014)	(0.013)	(0.017)
Numeracy Score	0.046***	0.032***	0.029***	0.027**	0.034**
	(0.017)	(0.011)	(0.009)	(0.012)	(0.017)
Openness	-0.024*	-0.010	-0.001	0.012	0.002
	(0.014)	(0.011)	(0.009)	(0.011)	(0.014)
Conscientiousness	-0.033**	-0.012	-0.001	-0.003	0.025*
	(0.016)	(0.010)	(0.008)	(0.010)	(0.015)
Extroversion	-0.009	-0.011	-0.009	0.002	-0.006
	(0.010)	(0.008)	(0.009)	(0.010)	(0.013)
Agreeableness	0.029*	0.023**	0.020**	0.018	0.005
	(0.017)	(0.011)	(0.008)	(0.014)	(0.015)
Emotional Stability	0.025*	-0.000	0.011	0.010	-0.006
	(0.014)	(0.010)	(0.010)	(0.012)	(0.014)
Hostile Bias	0.002	0.002	0.009	-0.001	0.004
	(0.015)	(0.011)	(0.010)	(0.009)	(0.016)
Decision Making	-0.024	-0.008	-0.007	-0.003	-0.002
	(0.015)	(0.011)	(0.009)	(0.011)	(0.015)
Constant	2.841***	3.004***	3.080***	3.168***	3.351***
	(0.065)	(0.044)	(0.033)	(0.051)	(0.056)
Observations	2150	2150	2150	2150	2150

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors based on 100 replications are reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Table 6: Gender-Specific Quantile Regressions (with firm specific 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	0.033	0.074	0.059	0.033	0.033	0.078*	0.043**	0.075***	0.049**	0.073**	0.045	0.084
	(0.030)	(0.083)	(0.036)	(0.059)	(0.024)	(0.044)	(0.020)	(0.023)	(0.024)	(0.029)	(0.042)	(0.067)
Years of education	-0.016	-0.057*	-0.032**	-0.066***	-0.037***	-0.054***	-0.019***	-0.057***	-0.009	-0.053***	-0.014	-0.065***
	(0.012)	(0.032)	(0.013)	(0.021)	(0.007)	(0.011)	(0.004)	(0.007)	(0.008)	(0.011)	(0.012)	(0.025)
Years of education squared/100	0.402***	0.588***	0.446***	0.660***	0.484***	0.585***	0.418***	0.588***	0.393***	0.549***	0.440***	0.621***
	(0.060)	(0.149)	(0.054)	(0.098)	(0.030)	(0.055)	(0.019)	(0.033)	(0.040)	(0.055)	(0.061)	(0.114)
Tenure in current firm	0.039***	0.052***	0.037***	0.045***	0.040***	0.042***	0.044***	0.051***	0.033***	0.050***	0.037***	0.061***
	(0.006)	(0.018)	(0.008)	(0.017)	(0.005)	(0.008)	(0.004)	(0.004)	(0.006)	(0.010)	(0.007)	(0.019)
Tenure in current firm squared/100	-0.069***	-0.073	-0.074**	-0.041	-0.078***	-0.040	-0.096***	-0.074***	-0.046*	-0.075	-0.042	-0.086
	(0.024)	(0.085)	(0.030)	(0.096)	(0.017)	(0.026)	(0.016)	(0.014)	(0.024)	(0.051)	(0.026)	(0.094)
Prior Experience	0.021	-0.025	0.008	0.013	0.014	0.005	0.018**	-0.030**	0.022*	-0.038	0.045***	-0.028
	(0.014)	(0.079)	(0.016)	(0.052)	(0.009)	(0.022)	(0.007)	(0.013)	(0.011)	(0.030)	(0.012)	(0.061)
Prior Experience squared/100	0.030	0.186	0.079	-0.007	0.049	0.012	0.035	0.235**	0.031	0.250	-0.030	0.200
	(0.056)	(0.269)	(0.069)	(0.304)	(0.037)	(0.148)	(0.037)	(0.110)	(0.047)	(0.443)	(0.044)	(0.734)
Reading Score	0.027	0.126*	0.057**	0.082*	0.046***	0.101***	0.017	0.126***	0.013	0.153***	0.017	0.156***
	(0.022)	(0.075)	(0.025)	(0.048)	(0.016)	(0.028)	(0.014)	(0.013)	(0.016)	(0.025)	(0.020)	(0.060)
Numeracy Score	0.048*	-0.015	0.063***	-0.019	0.045***	-0.016	0.032***	-0.016	0.036**	-0.014	0.027	-0.015
	(0.026)	(0.036)	(0.016)	(0.030)	(0.013)	(0.022)	(0.008)	(0.011)	(0.014)	(0.022)	(0.021)	(0.049)
Openness	-0.007	-0.041	-0.023	-0.007	-0.015	-0.023	0.000	-0.041***	0.014	-0.058***	-0.017	-0.100***
	(0.014)	(0.055)	(0.019)	(0.035)	(0.010)	(0.023)	(0.008)	(0.014)	(0.014)	(0.022)	(0.018)	(0.038)
Conscientiousness	-0.008	0.044	-0.032*	0.053**	-0.017	0.043**	-0.000	0.045***	-0.005	0.038**	0.026*	0.017
	(0.017)	(0.043)	(0.017)	(0.025)	(0.011)	(0.017)	(0.007)	(0.007)	(0.012)	(0.015)	(0.014)	(0.030)
Extroversion	-0.007	-0.012	-0.006	0.011	-0.019**	-0.041**	-0.012*	-0.013	0.002	0.009	-0.008	0.043
	(0.013)	(0.039)	(0.015)	(0.028)	(0.009)	(0.018)	(0.007)	(0.010)	(0.010)	(0.013)	(0.012)	(0.027)
Agreeableness	0.008	0.102**	0.027	0.055*	0.024*	0.067***	0.011	0.103***	-0.003	0.100***	-0.012	0.137***
	(0.015)	(0.044)	(0.020)	(0.032)	(0.013)	(0.017)	(0.009)	(0.011)	(0.012)	(0.018)	(0.015)	(0.039)
Emotional Stability	0.006	-0.018	0.030	-0.008	-0.003	-0.009	0.006	-0.018*	0.012	-0.035*	-0.015	-0.044
	(0.012)	(0.032)	(0.018)	(0.028)	(0.011)	(0.017)	(0.010)	(0.009)	(0.012)	(0.020)	(0.015)	(0.042)
Hostile Bias	0.001	-0.002	-0.009	0.070**	-0.003	0.030	0.008	-0.004	0.007	-0.027	0.004	-0.012
	(0.013)	(0.037)	(0.017)	(0.030)	(0.010)	(0.022)	(0.007)	(0.012)	(0.013)	(0.018)	(0.017)	(0.034)
Decision Making	-0.007	0.021	-0.038**	-0.007	-0.013	0.003	-0.007	0.021**	-0.010	0.034	0.015	0.029
	(0.015)	(0.049)	(0.017)	(0.042)	(0.012)	(0.022)	(0.008)	(0.010)	(0.014)	(0.024)	(0.016)	(0.039)
Constant	3.074***	3.147***	2.832***	2.827***	3.017***	2.977***	3.055***	3.155***	3.191***	3.284***	3.314***	3.407***
	(0.070)	(0.188)	(0.083)	(0.129)	(0.046)	(0.079)	(0.030)	(0.052)	(0.048)	(0.072)	(0.075)	(0.165)
Observations	1730	420	1730	420	1730	420	1730	420	1730	420	1730	420

Note: Dependent variable is log of current hourly wage. Bootstrapped standard errors based on 100 replications 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	51.9	48.1	64.5	35.5
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	52.3	47.7	66.1	33.9
Panel C: Adding personality scores					
Male non-discriminatory structure	0.116	0.06	0.056	0.038	0.078
Female non-discriminatory structure	0.116	0.061	0.055	0.08	0.036
Pooled (Neumark) non-discriminatory structure	0.116	0.062	0.053	0.091	0.025
% of wage gap (Neumark)	100	53.9	46.1	78.2	21.8

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 scores are also included.

Table 8: Quantile Decompositions of Log Wage Gaps

Percentile	Col.1 Difference	Col.2 Characteristics	Col.3 Coefficients
Panel A: Only socio-economic characteristics			
10	0.192	0.063	0.129
	(0.012)	(0.022)	(0.022)
25	0.193	0.076	0.117
	(0.01)	(0.019)	(0.021)
50	0.171	0.082	0.089
	(0.011)	(0.022)	(0.023)
75	0.132	0.091	0.041
	(0.012)	(0.029)	(0.03)
90	0.063	0.117	-0.054
	(0.017)	(0.04)	(0.038)
Panel B: Adding cognitive skills			
10	0.198***	0.063**	0.135***
	(0.01)	(0.026)	(0.026)
25	0.194***	0.08***	0.113***
	(0.009)	(0.02)	(0.021)
50	0.17***	0.085***	0.085***
	(0.011)	(0.021)	(0.022)
75	0.128***	0.092***	0.036
	(0.013)	(0.025)	(0.031)
90	0.069***	0.119***	-0.049
	(0.019)	(0.041)	(0.043)
Panel C: Adding personality scores			
10	0.187***	0.019	0.168***
	(0.018)	(0.043)	(0.034)
25	0.167***	0.042	0.125***
	(0.014)	(0.032)	(0.027)
50	0.111***	0.052	0.059*
	(0.013)	(0.032)	(0.036)
75	0.091***	0.084*	0.007
	(0.016)	(0.039)	(0.045)
90	0.063***	0.107*	-0.044
	(0.024)	(0.059)	(0.064)

Note: Bootstrapped standard errors based on 100 replications reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%. Panel A includes education, tenure, experience and the squared terms. Panel B further adds standardized scores for cognitive skills. In Panel C, standardized personality scores are also included.

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

Percentile	Col.1 Difference	Col.2 Characteristics	Col.3 Coefficients
Panel A: Only socio-economic characteristics			
10	0.178***	0.063***	0.115***
	(0.009)	(0.016)	(0.015)
25	0.176***	0.081***	0.095***
	(0.008)	(0.016)	(0.015)
50	0.149***	0.082***	0.067***
	(0.01)	(0.018)	(0.022)
75	0.113***	0.089***	0.024
	(0.015)	(0.023)	(0.035)
90	0.102***	0.122***	-0.02
	(0.017)	(0.033)	(0.039)
Panel B: Adding cognitive skills			
10	0.175***	0.066***	0.109***
	(0.009)	(0.016)	(0.016)
25	0.176***	0.081***	0.095***
	(0.008)	(0.016)	(0.016)
50	0.149***	0.085***	0.064***
	(0.01)	(0.018)	(0.024)
75	0.109***	0.088***	0.021
	(0.015)	(0.022)	(0.034)
90	0.101***	0.118***	-0.017
	(0.017)	(0.033)	(0.037)
Panel C: Adding personality scores			
10	0.171***	0.009	0.162***
	(0.013)	(0.03)	(0.028)
25	0.146***	0.035	0.111***
	(0.013)	(0.026)	(0.029)
50	0.092***	0.049	0.043
	(0.017)	(0.029)	(0.039)
75	0.064***	0.089**	-0.025
	(0.021)	(0.033)	(0.038)
90	0.064***	0.126**	-0.061
	(0.022)	(0.049)	(0.055)

Note: Bootstrapped standard errors based on 100 replications reported in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%. Panel A includes education, tenure, experience and the squared terms. Panel B further adds standardized scores for cognitive skills. In Panel C, standardized personality scores are also included.

Table 10: Within-firm gender wage gap

	Col.1	Col.2	Col.3	Col.4
Education	-0.199**	-0.189*	-0.189*	-0.176
	(0.092)	(0.106)	(0.110)	(0.116)
Finance	-0.167**	-0.186**	-0.160	-0.161
	(0.084)	(0.093)	(0.097)	(0.102)
Manufacturing	-0.207	-0.280**	-0.180	-0.243
	(0.125)	(0.138)	(0.142)	(0.151)
Public Admn	-0.104	-0.110	-0.086	-0.092
	(0.103)	(0.118)	(0.119)	(0.125)
21-70 employees	-0.108	-0.077	-0.094	-0.082
	(0.070)	(0.064)	(0.072)	(0.071)
71 or more employees	-0.131*	-0.076	-0.110	-0.071
	(0.067)	(0.065)	(0.073)	(0.069)
Age of firm	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
% of females	0.310*	0.290	0.311	0.240
	(0.182)	(0.199)	(0.205)	(0.211)
% of top mgmt females	-0.486***	-0.422**	-0.414**	-0.385*
	(0.170)	(0.188)	(0.183)	(0.198)
Formal performance review	0.001	0.005	0.009	0.020
	(0.045)	(0.049)	(0.047)	(0.050)
Firm is profitable	0.048	0.035	0.049	0.034
	(0.055)	(0.056)	(0.054)	(0.057)
Firm exports	0.021	0.053	0.043	0.053
	(0.079)	(0.084)	(0.081)	(0.085)
Female manager	-0.187**	-0.192**	-0.202**	-0.190*
	(0.089)	(0.094)	(0.091)	(0.097)
Manager college educated	-0.153	-0.184*	-0.164	-0.180*
	(0.106)	(0.103)	(0.103)	(0.096)
Value non-cognitive skills for non-professionals	0.131**			
	(0.057)			
Value non-cognitive skills for professionals	0.012			
	(0.047)			
Importance given for non-professionals:				
Communication skills		-0.044		-0.102*
		(0.038)		(0.057)
Team work skills		-0.029		-0.015
		(0.033)		(0.035)
Problem solving skills		0.086**		0.099**
		(0.039)		(0.049)
Literacy skills		-0.029		-0.040
		(0.045)		(0.055)
Numeracy skills		-0.011		-0.008
		(0.035)		(0.043)
Customer care skills		-0.001		-0.006
		(0.035)		(0.040)
Responsibility		0.018		0.019
		(0.037)		(0.047)
Creativity		-0.015		-0.038
		(0.031)		(0.042)
Vocational job-specific skills		-0.015		-0.012
		(0.035)		(0.059)
Importance given for professionals:				
Communication skills			0.002	0.061
			(0.031)	(0.047)
Team work skills			0.002	0.020
			(0.034)	(0.034)
Problem solving skills			-0.018	-0.055
			(0.034)	(0.040)
Literacy skills			-0.009	0.007
			(0.033)	(0.041)
Numeracy skills			-0.004	0.001
			(0.033)	(0.042)
Customer care skills			-0.021	-0.005
			(0.038)	(0.039)
Responsibility			0.022	-0.006
			(0.033)	(0.044)
Creativity			0.045	0.053
			(0.034)	(0.044)
Vocational job-specific skills			-0.031	-0.005
			(0.030)	(0.053)
Observations	164	164	164	164
R^2	0.189	0.218	0.189	0.256

Note: Robust standard errors in parentheses. *** significant at 1%,** significant at 5%,* significant at 10%.

Appendix:

How do you see yourself?
Response scale: Almost always, most of the time, some of the time, almost never

Agreeableness:
Are you very polite to other people?
Are you generous to other people with your time or money?
Do you forgive other people easily?

Conscientiousness:
When doing a task, are you very careful?
Do you work very well and quickly?
Do you prefer relaxation more than hard work?

Neuroticism:
Are you relaxed during stressful situations?
Do you tend to worry?
Do you get nervous easily?

Extraversion:
Are you talkative?
Are you outgoing and sociable, for example, do you make friends very easily?
Do you like to keep your opinions to yourself? Do you prefer to keep quiet when you have an opinion?

Openness:
Do you come up with ideas other people haven't thought of before?
Are you very interested in learning new things?
Do you enjoy beautiful things, like nature, art and music?

Hostile Attribution Bias:
Do people take advantage of you?
Are people mean/not nice to you?

Decision-making:
Do you think about how the things you do will affect you in the future?
Do you think carefully before you make an important decision?
Do you ask for help when you don't understand something?

Do you think about how the things you do will affect others?