

Nordman, Christophe J.; Sarr, Leopold R.; Sharma, Smriti

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WIDER Working Paper 2018/77

Skills, personality traits, and gender wage gaps

Evidence from Bangladesh

Christophe Jalil Nordman,¹ Leopold Sarr,² and Smriti Sharma³

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Abstract: We use a recent first-hand linked employer-employee survey covering the formal sector of Bangladesh to explain gender wage gaps by the inclusion of measures of cognitive attainment and personality traits. Our results show that cognitive skills have greater explanatory power than personality traits in determining mean wages. Unconditional quantile regressions show that cognitive attainment as measured by reading and numeracy seems to confer different benefits on women and men respectively. The Big Five trait of agreeableness is positively associated with females' wages across the wage distribution. Decompositions show that about 30–40 per cent of the wage gap can be explained by characteristics along the wage distribution. Cognitive skills cumulatively account for a larger share of the explained component than personality traits do, and matter more at lower percentiles. However, together these cognitive and socio-emotional skills matter to a lesser degree than factors such as one's tenure in the firm.

Keywords: Gender wage gap, cognitive skills, personality traits, matched worker-firm data, Bangladesh

JEL classification: J16, J24, J31, J71, C21, O12

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¹ Institute for Research Development, Développement Institutions et Mondialisation (DIAL), and French Institute of Pondicherry, Pondicherry, India, corresponding author: nordman@dial.prd.fr; ² SMJDATA, Fairfax, Virginia, USA; ³ UNU-WIDER, Helsinki, Finland.

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1 Introduction

Socio-emotional skills have recently received significant attention as determinants of labour market performance. In fact, these traits, referring to qualities such as motivation, leadership, self-esteem, social skills, etc., have in some cases been shown to be almost as important as cognitive skills for wages and employment prospects (e.g., Heckman et al. 2006; Lindqvist and Vestman 2011). Socio-emotional skills can affect productivity directly by being considered part of an individual's set of endowments or serving as incentive-enhancing preferences (Bowles et al. 2001; Deming 2017). Additionally, they can indirectly affect productivity, for instance through effects on occupational choice and educational attainment (e.g., Cobb-Clark and Tan 2011; Lundberg 2013).

There is a growing body of literature that has explored gender differences in personality traits as potential alternative explanations for the gender wage gap.¹ However, the existing evidence is based predominantly on developed economies, with results indicating some variation in the contribution of these traits to wage gaps. For instance, Mueller and Plug (2006) find that three per cent of the gender wage gap in the USA is explained by differences in the Big Five personality traits. On the other hand, Fortin (2008) reports that eight per cent of the gender wage gap in the USA is explained by differences in socio-emotional 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 the Netherlands Nyhus and Pons (2005) find that wage returns to Big Five personality traits vary by gender. While there exists literature on estimating gender wage gaps in developing countries (e.g., Ahmed and Maitra 2015; Chi and Li 2008; Nordman and Roubaud 2009; Nordman et al. 2011), evidence documenting the influence of cognitive and socio-emotional skills on gender wage gaps in a developing country context is scarce, primarily due to data limitations.

In this paper, we attempt to address this gap in the literature by using linked employer-employee data from a rapidly growing country, namely Bangladesh. This survey is novel in that it measures these cognitive skills and personality traits using detailed tests among a sample of employees within firms that are representative of the Bangladeshi formal sector. Our paper is among the first to contribute to understanding the importance of differences in cognitive and socio-emotional skills for explaining gender wage gaps in a developing country.² This question is relevant in the context of developing countries such as Bangladesh, as the prevalence of gender norms and societal expectations about gender-appropriate behaviour may influence employers' perceptions and valuations of skills and traits differently for males and females, leading to differences in labour market returns. While gender-differentiated returns have been observed even in some developed country settings (e.g., Manning and Swaffield 2008; Mueller and Plug 2006), it is pertinent to know whether similar observations can be made using developing country data in the presence of culturally rooted gender norms and attitudes towards women in South Asia (Jayachandran 2015).

In terms of methodology, we conduct a distributional analysis of gender wage gaps, as analysing gaps at the means of men's and women's wages may only reveal part of the prevailing gender

¹ Blau and Kahn (2017) summarize the key findings of this literature using data from developed countries. Further, a large experimental literature shows that men and women tend to differ in behavioural traits such as competitiveness, risk preferences, and attitudes towards negotiation, factors that can possibly explain gender differences in labour market outcomes (for reviews, see Bertrand 2011; Blau and Kahn 2017).

² Diaz et al. (2013) estimate that grit and some of the Big Five traits result in earning gains of between five and 10 per cent in urban Peru, and Glewwe et al. (2017) find no evidence that socio-emotional skills matter for wage determination in rural China. However, neither study examines the salience of these traits for gender wage gaps.

inequality. We adopt the unconditional quantile regression-based decomposition of Firpo et al. (2009), which separates the gender wage gap into explained and unexplained components at various points of the wage distribution and allows for detailed decompositions to assess the importance of individual covariates for the wage gap. This represents a methodological improvement over the traditional quantile decompositions, which rely on conditional quantile regressions.³

Further, the linked employer-employee nature of the data set represents an advantage over household-level data, which typically do not allow one to observe firm characteristics that can often have important implications for wage inequality.⁴ A priori, including firm-specific effects should alter the magnitude of the gender wage gap if (i) the wage gap is correlated with the firms' observed and unobserved characteristics, and (ii) the wage gap between males and females is due to gender-based sorting of workers across firms that pay different wages. For instance, Cardoso et al. (2016) show that the glass ceiling effect (i.e. a higher gender wage gap at the upper end of the wage distribution) in Portugal arises mainly through the allocation of workers to firms such that females have lower access to high-paying firms. There is also evidence of gender segregation across firms in the African manufacturing sector (Fafchamps et al. 2009) and in small firms in the USA (Carrington and Troske 1995). If there are high-paying firms that hire more men and low-paying firms hiring more women, then firms' characteristics will influence the gender differences in wages. Controlling for firm heterogeneity—through firm-specific effects—should then reduce the magnitude of the gender wage gap.

Our analysis finds that cognitive skills matter more than personality traits in determining mean wages. Unconditional quantile regressions show that cognitive attainment as measured by reading and numeracy seems to confer different benefits on women and men respectively. The Big Five personality trait of agreeableness matters positively for females' wages across the wage distribution. On the other hand, personality traits do not matter for wage determination among males. Decompositions show that about 30–40 per cent of the wage gap can be explained by characteristics along the wage distribution. In line with regression analyses, we find that cognitive skills cumulatively account for a larger share of the explained component than personality traits do, and the trait of agreeableness mitigates the gender wage gap. However, together these cognitive and socio-emotional skills matter much less than factors such as one's tenure or length of employment in the firm.

The paper is organized as follows. The next section discusses the empirical framework. Section 3 describes the data. Section 4 presents the descriptive statistics and results from regression and decomposition analyses. Finally, Section 5 offers concluding comments.

2 Empirical framework

We first use the method of Blinder (1973) and Oaxaca (1973) to decompose the mean wage gap between males and females into portions attributable to differences in the distribution of endowments (the explained component or composition effect) and differences in returns to these endowments (the unexplained component or wage structure effect). This methodology involves

³ See Fortin et al. (2011) for a review of decomposition methods in economics.

⁴ A caveat is that employer-employee data are not representative of the broader population. However, to the extent that the firms' characteristics matter for wage formation, the inclusion of firm-specific effects is advantageous for studying wage gaps.

estimating wage equations separately for males (m) and females (f). The resulting decomposition is:

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

where the outcome 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 wage 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 returns to characteristics.

As it is not a priori clear which group's coefficients (β) should be chosen as the reference non-discriminatory wage structure, following Fortin (2008), we use the reference wage structure where the male advantage equals the female disadvantage by including a gender intercept.⁵ This decomposition is therefore compatible with the standard practice of including a dummy for the group of interest (i.e. female) in a pooled regression, where the coefficient on the female dummy is interpreted as a measure of the unexplained gender wage gap. Jann (2008) explains that this avoids distorting the decomposition because of any transfers of the unexplained gap over into the slope parameters of the pooled model.

We further examine how the wage gap between males and females evolves along the whole wage distribution. The Blinder-Oaxaca method cannot be directly applied for decomposing the gap across quantiles, as the law of iterated expectations does not hold for quantiles, i.e. $Q_\theta(w) \neq E(Q_\theta(w)|X) = E(X)\beta_\theta$, where Q_θ is the unconditional quantile.

Firpo et al. (2009) generalize the Blinder-Oaxaca mean decomposition to quantiles by using unconditional quantile regressions (UQR). UQR is based on the concept of recentred influence function (RIF).⁶ In a RIF regression, the outcome variable is replaced by the RIF of the statistic of interest (mean, quantiles, etc.). Consider $IF(w, v)$, the influence function corresponding to observed log wage (w) for the distributional statistic $v(F_w)$. The RIF is defined as $RIF(w; v) = v(F_w) + IF(w; v)$ such that it aggregates back to the statistic of interest ($\int RIF(w; v) * dF(w) = v(F_w)$). By assuming a linear relationship between the RIF and explanatory variables, we can then use the Blinder-Oaxaca method to carry out aggregate and detailed decompositions of the gap between groups at the unconditional θ^{th} quantiles. The RIF for the quantile θ of log wage (w) is given by:

$$RIF(w, Q_\theta) = Q_\theta + [w - d_\theta]/f_w(Q_\theta) \quad (2)$$

where $f_w(Q_\theta)$ is the density distribution function of w at Q_θ , and d_θ is a binary variable taking value 1 if $w \leq Q_\theta$ and 0 otherwise. The $RIF(w, Q_\theta)$ satisfies the following properties: (i) its mean is equal to the actual θ^{th} quantile $E_w[RIF(w, Q_\theta)] = Q_\theta$; (ii) the mean of the expectation

⁵ This represents an improvement over the pooled reference wage structure proposed by Neumark (1988), as pooled coefficients capture part of the between male and female effects, thus assigning more importance to covariates with large gender differences.

⁶ The conditional quantile regression-based decomposition of Machado and Mata (2005) has a number of drawbacks. First, it does not allow for dividing up the explained component into the contribution of each single covariate. Second, it is computationally intensive, as it involves estimating many quantile regressions and large-scale simulations. Third, the decomposition is only consistent if the correct functional form is used for each quantile, and this can be empirically challenging.

conditional on X is equal to the actual θ^{th} quantile $E_X[E_w[RIF(w, Q_\theta)|X]] = Q_\theta$. This implies that we can obtain the decomposition of the gap at quantiles by using a Blinder-Oaxaca decomposition in which the dependent variable w is replaced by $RIF(w, Q_\theta)$.

$$\overline{RIF(w, Q_\theta)^m} - \overline{RIF(w, Q_\theta)^f} = \bar{X}^m \hat{\beta}_\theta^m - \bar{X}^f \hat{\beta}_\theta^f = (\bar{X}^m - \bar{X}^f) \hat{\beta}_\theta^m + \bar{X}^f (\hat{\beta}_\theta^m - \hat{\beta}_\theta^f) \quad (3)$$

Given that properties (i) and (ii) above hold, we get the following, where the first term on the right-hand side represents the explained component, and the second is the unexplained residual component:

$$Q_\theta^m - Q_\theta^f = (\bar{X}^m - \bar{X}^f) \hat{\beta}_\theta^m + \bar{X}^f (\hat{\beta}_\theta^m - \hat{\beta}_\theta^f) \quad (4)$$

This allows us to arrive at a detailed decomposition where we can evaluate the contribution of each covariate:

$$Q_\theta^m - Q_\theta^f = \sum_{k=1}^K (\bar{x}_k^m - \bar{x}_k^f) \hat{\beta}_{\theta k}^m + \bar{X}^f (\hat{\beta}_\theta^m - \hat{\beta}_\theta^f) \quad (5)$$

3 Data

The Bangladesh Enterprise-Based Skills Survey (ESS) for 2012 was sponsored by the World Bank and carried out by the South Asia Human Development Sector (Nomura et al. 2013), including two authors of this paper.⁷ The survey is representative of firms in the formal sector.⁸ The ESS is a linked employer-employee survey, containing an employer survey as well as an employee survey for a random subsample of employees within the surveyed firms. The employer survey, administered to business owners or senior managers at 500 firms, consists of a general enterprise profile, including characteristics of the firm and its managers, and its recruitment and training practices. The employee survey, administered to 6,981 employees, comprises detailed information on their education, work experience, and family background, and contains tests to assess their cognitive and socio-emotional skills.⁹ The surveys were conducted between November 2012 and January 2013 through face-to-face interviews in Bangla.

Cognitive attainment of employees is measured through literacy and numeracy tests consisting of eight questions each.¹⁰ The literacy test includes ability to read words and sentences, punctuation, comprehension of short paragraphs and conversations, and translation from Bangla to English and vice versa. The numeracy test consists of simple mathematical operations (addition,

⁷ 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. The sampling methodology for the ESS is stratified random sampling, with the strata being economic sector and firm size. From a roster of employees provided by the firm, random sampling is done such that more employees are drawn from larger firms. Note that the respondent for the employer survey is not interviewed in the employee survey.

⁸ While the Bangladeshi economy has a high proportion of informality, the formal sector is an important driver of employment and productivity, making this a relevant sector to study. Further, within such a context, data on cognitive and socio-emotional skills are quite rare.

⁹ The questionnaire for cognitive and socio-emotional skills is available in Annex 2 of Nomura et al. (2013).

¹⁰ Cunningham and Villasenor (2016) classify cognitive skills as follows: basic cognitive, higher-order cognitive, and technical/job-specific.

subtraction, multiplication, and division), unit conversion, measurement, and cost calculation. Scores are calculated by assigning one point for each correct answer, and then standardized. A potential caveat is that these questions assess basic cognitive skills that comprise academic knowledge, and not higher-order cognitive skills related to problem-solving and complex information-processing.

Employees' personality traits are assessed through a battery of questions—taken from the World Bank 'Skills Toward Employment and Productivity' surveys—asking them to answer on a four-point scale ranging from 'almost always' to 'almost never'. Of these questions, 15 items measure the following five personality factors or traits, commonly identified as the Big Five: *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 having an outward orientation rather than being reserved; *agreeableness* is related to the tendency to act in a cooperative and unselfish manner; and *neuroticism* (the 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 is defined as over-attributing hostile intent to peers' behaviours even when the actual intent is benign or ambiguous. Finally, four questions adapted from the Melbourne Decision-Making Scale were used to assess *decision-making*, that is, whether individuals think about the future consequences of their decisions, and whether they consider multiple options when making decisions. Traits are measured by taking the average standardized score on items corresponding to each trait.

Since we are interested in within-firm gender wage gaps, we consider firms where at least one male and one female employee have been interviewed to enable the use of firm fixed effects, and where we have data on all variables to be included in the analysis. This results in a working sample of 225 firms and 2,150 employees.¹¹ To understand the correlates of item non-response, we regress survey completion on socio-economic characteristics and cognitive skills (results not shown). We do not find any of the characteristics to be systematically or significantly correlated with survey completion.¹²

We now note some sources of bias that might arise in our analysis. First, given the likely error in the measurement of skills, our estimates would be subject to classical attenuation bias and should be interpreted as lower bounds. Second, since wages and personality traits are measured contemporaneously, reverse causality can occur if wages affect skill accumulation.¹³ In this case, our estimates of returns to skills will be biased upwards. However, as we discuss in Section 4.1, the average employee in our sample is 32 years old, falling into the working-age range, during which personality traits are most stable and any changes have been found to not be economically significant (Cobb-Clark and Schurer 2012). Finally, omitted variables bias may arise if unobserved characteristics drive both wages and skills. A positive (negative) correlation of skills with other

¹¹ The large reduction in the sample of firms is mainly due to 236 firms being dropped where either no females or no males were interviewed. Further, we lose some employee-level observations due to incomplete responses on only the personality traits.

¹² We also try to deal with missing data concerns by using the multiple imputation (MI) method. MI, a simulation-based approach, imputes missing data while recognizing the uncertainty associated with imputed values (Little and Rubin 2002). Dealing with item non-response in this way does not alter our findings. Results are available from the authors upon request.

¹³ Almlund et al. (2011) discuss how addressing the potential problem of reverse causality by using previously measured traits as predictors of later outcomes can lead to errors in variables if the traits evolve over time.

unobserved variables would bias the returns to skills upwards (downwards). Therefore, one should be conservative in interpreting the results as causal estimates.

An important caveat is that we only observe these formal-sector firms and their employees. Therefore, we are unable to account for the non-random selection of workers into the formal sector, and all estimated wage gaps reported in the paper should be interpreted as conditional on formal-sector employment.¹⁴ Previous work finds that there is positive selection into the formal sector based on skills (e.g., Acosta et al. 2015; Cobb-Clark and Tan 2011). Because of this, our estimated coefficients in wage regressions are likely to be attenuated, resulting in lower bounds. Further, as positive selection into the formal sector is likely to be more important for women than for men (e.g., Kingdon 1998; Olivetti and Petrongolo 2008), the observed gender wage gap understates the gap that would be observed if there were no gender differences in selection. In this case, the estimated returns to skills in our analysis would be more attenuated for females than for males. Therefore, the difference in skill returns between males and females should be larger and the unexplained component greater than we would observe for the overall employed population.

4 Results

4.1 Descriptive statistics

We begin with descriptive statistics of firm characteristics, listed in Table 1. About 71 per cent of firms report themselves as being profitable in the last year. On average, there are 193 employees per firm, of which 25 per cent are females. About 32 per cent 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 38 per cent respectively. Sixty-one per cent of senior managers in firms have a postgraduate degree. Only a paltry four per cent of firms have females as senior managers. Ninety-seven per cent of firms maintain either formal or informal accounts, and 96 per cent of firms are registered with the government, indicating a high level of formality.

In terms of industrial sectors, the largest share of firms (32 per cent) is engaged in manufacturing. Public administration and education make up 20–22 per cent each. Finance firms constitute 19 per cent, while commerce represents the remaining seven per cent. Further, among the manufacturing firms, textiles and apparel are the dominant activities, comprising 37 and 27 per cent respectively, while food products make up 17 per cent. More than half of the firms are based in Dhaka, the capital city. Chittagong, the second-largest city in Bangladesh, has 10 per cent of the firms, and Rajshahi and Rangpur account for eight and nine per cent of firms respectively.

¹⁴ According to the 2010 Bangladesh Labour Force Survey, 12 per cent of the employed workforce is in the formal sector, and the shares of males and females are 14.5 per cent and eight per cent respectively.

Table 1: Descriptive statistics of firm characteristics

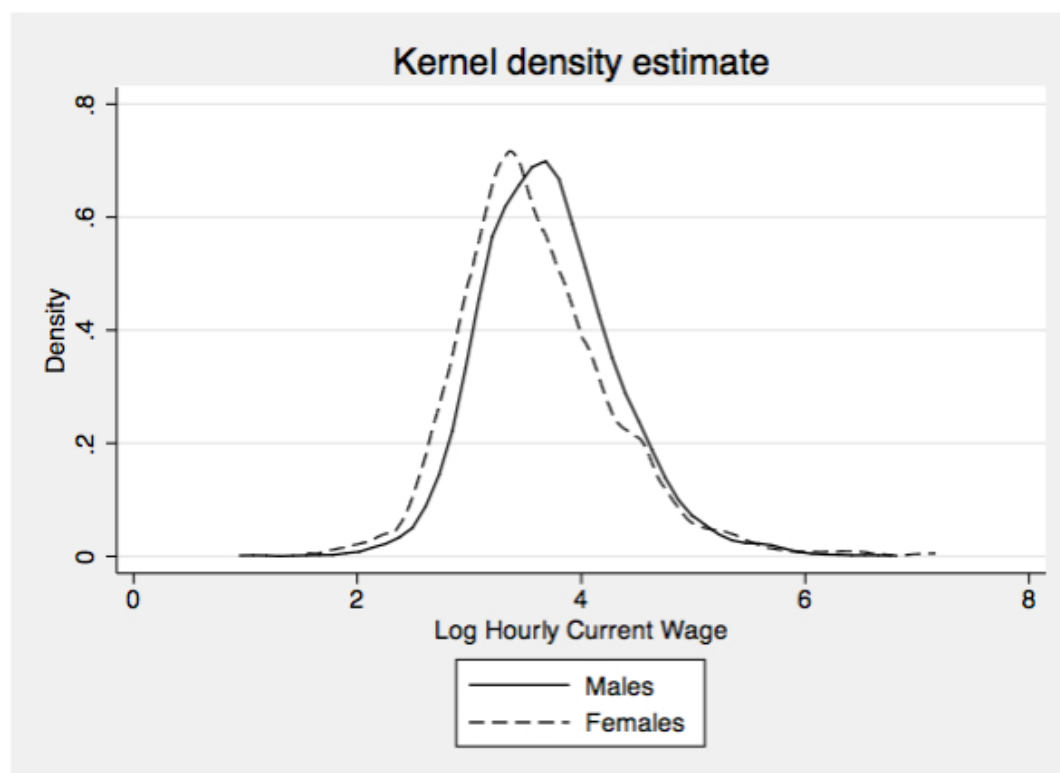
Variable	Mean	Standard deviation
Making profit (=1)	0.71	0.45
Number of employees	192.8	810.8
Share of female employees	0.25	0.17
Senior manager: female	0.04	0.19
Senior manager: postgraduate education	0.61	0.49
Small (10–20 employees)	0.324	0.47
Medium (21–70 employees)	0.298	0.46
Large (71+ employees)	0.378	0.49
Maintain formal or informal accounts	0.97	0.16
Registered with government	0.96	0.21
Sector: commerce	0.067	0.25
Sector: education	0.227	0.42
Sector: finance	0.191	0.39
Sector: manufacturing	0.316	0.46
Sector: public administration	0.2	0.4
Location: Rajshahi	0.093	0.29
Location: Khulna	0.071	0.26
Location: Dhaka	0.56	0.5
Location: Chittagong	0.102	0.3
Location: Barisal	0.049	0.22
Location: Sylhet	0.044	0.21
Location: Rangpur	0.08	0.27
Number of firms	225	

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

Proceeding to employee characteristics in Table 2, out of 2,150 employees, 420 are female, constituting 19.5 per cent of the employee sample.¹⁵ Males are two years older than females (two-sided t-test; p-value < 0.01), but there is no significant difference in the proportion of married males and females (p-value = 0.83). Twenty-nine per cent of employees have completed post-secondary education, and the remainder are evenly distributed across the other levels of education, i.e. higher secondary, secondary, junior secondary, and primary or below. In terms of gender differences in education, we find that the share of females with a primary or lower level of education is significantly higher than that of males (p-value = 0.003), but we do not observe any other significant differences. Males also exhibit significantly greater tenure at their current firm (p-value = 0.02) and greater experience prior to joining their current firm (p-value = 0.04). Given these differences in endowments, a priori a higher wage for men is expected, and we find that males earn on average significantly higher hourly wages than females (p-value < 0.01). We also find that there exists a wage gap at various other critical points of the wage distribution, with males earning more than females. As seen in Figure 1, the male wage distribution lies to the right of the female distribution; a Kolmogorov-Smirnov test shows them to be significantly different (p-value < 0.01).

¹⁵ Lack of overlap or common support in the distributions of covariates between males and females can lead to a problem when one compares incomparable individuals and out-of-sample extrapolations of the wage gap. However, we find that all males and females in our sample lie in the region of common support. Results are available from the authors upon request. We thank an anonymous reviewer for suggesting this check.

Figure 1: Hourly wage distributions by gender



Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

Moving on to cognition as measured by reading and numeracy tests, our data show that men outperform women significantly in terms of numeracy score (p -value < 0.01) and reading score (p -value = 0.099), although the difference in the latter is only weakly significant. Finally, in line with the literature documenting gender differences in personality traits (Costa et al. 2001; Feingold 1994), females report significantly higher standardized scores on agreeableness (p -value = 0.057) and lower scores on emotional stability (p -value = 0.006) compared with men. They also score higher on openness to experience (p -value = 0.002), decision-making (p -value = 0.001), and hostile bias (p -value = 0.005). Men score higher on extroversion and conscientiousness, but the gender differences are not statistically significant.

In terms of occupational distributions, while 4.6 per cent of males and 2.6 per cent of females are in managerial roles, approximately 19 per cent of males and females are in professional positions. Further, while almost 21 per cent of women are in unskilled elementary occupations, the proportion of men is 13 per cent.

Table 2: Descriptive statistics of employee characteristics

Variable	All	Males	Females	P-value of t-tests of male-female difference
Wages:				
Ln (Hourly wage) – mean	3.69 (0.63)	3.72 (0.61)	3.6 (0.69)	0.00
Ln (Hourly wage) – p10	2.993	3.033	2.831	
Ln (Hourly wage) – p25	3.262	3.282	3.178	
Ln (Hourly wage) – p50	3.626	3.657	3.495	
Ln (Hourly wage) – p75	4.042	4.063	3.957	
Ln (Hourly wage) – p90	4.491	4.495	4.476	
Right-hand side characteristics:				
Age	32.26 (8.49)	32.62 (8.51)	30.81 (8.27)	0.00
Married	0.8 (0.4)	0.8 (0.4)	0.8 (0.4)	0.83
Primary and below education	0.18 (0.38)	0.17 (0.38)	0.23 (0.42)	0.003
Junior secondary education	0.16 (0.37)	0.17 (0.37)	0.135 (0.34)	0.10
Secondary education	0.18 (0.38)	0.19 (0.39)	0.16 (0.37)	0.21
Higher secondary education	0.18 (0.38)	0.18 (0.39)	0.185 (0.39)	0.88
Post-secondary education	0.29 (0.45)	0.29 (0.45)	0.28 (0.45)	0.8
Tenure in current firm	5.94 (6.08)	6.09 (6.17)	5.3 (5.66)	0.02
Years of prior experience	1.92 (2.93)	1.98 (3.01)	1.65 (2.58)	0.04
Reading test score	4.95 (2.54)	5.01 (2.49)	4.77 (2.75)	0.099
Numeracy test score	5.76 (1.99)	5.84 (1.94)	5.44 (2.17)	0.00
Openness to experience	2.6 (0.59)	2.59 (0.59)	2.68 (0.59)	0.002
Conscientiousness	2.86 (0.58)	2.87 (0.57)	2.83 (0.58)	0.2
Extroversion	2.32 (0.49)	2.32 (0.5)	2.33 (0.49)	0.63
Agreeableness	2.57 (0.58)	2.56 (0.57)	2.62 (0.6)	0.06
Emotional stability	2.71 (0.56)	2.73 (0.56)	2.65 (0.56)	0.006
Hostile bias	2.38 (0.73)	2.36 (0.72)	2.47 (0.74)	0.005
Decision-making	2.56 (0.55)	2.54 (0.55)	2.64 (0.54)	0.001
Number of employees	2,150	1,730	420	

Notes: Standard deviation reported in parentheses. Wages reported in taka. Maximum score for reading and numeracy tests is 8. Maximum score for personality traits is 4. P-values based on two-sided t-tests comparing males and females.

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

4.2 The mean gender wage gap

We first estimate ordinary least squares (OLS) regressions for the pooled sample of males and females and cluster the standard errors at the firm level. 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 gender (takes the value 1 if the employee is male, and 0 otherwise), marital status, levels of completed education (a binary variable for each level of education, with primary and lower levels of education being the omitted group), years of prior experience, years of tenure, and their quadratic effects. In the second set, we further include standardized scores on the reading and numeracy tests. In the third set, to measure personality traits, we also include standardized scores on each of the Big Five traits (extroversion, agreeableness, conscientiousness, openness to experience, and emotional stability), hostile bias, and decision-making. Cognitive skills and personality traits are measures of employees' (usually unobserved) ability. Hence, we do not try to correct for endogeneity of human capital variables using instruments or the control function approach (Wooldridge 2002). The lack of plausible instruments is one reason; but also we believe that this addition of cognitive skills and personality traits represents an added value compared with other studies that rely on a control function approach to estimate returns to education (Kuepie et al. 2009; Söderbom et al. 2006), because here we can partly control for employees' ability, somewhat purging the wage equation of the omitted ability bias.¹⁶ Next, in each of these regressions, we can pick up the role of unobserved firm heterogeneity by introducing firm dummies into the regression.

The OLS results are in Table 3. In Column 1, we regress the log wage on the male dummy only and obtain a positive coefficient indicating a significant raw gender wage gap of 11.6 per cent in favour of men. In Column 2, when we add the socio-economic controls, the male coefficient falls to 7.3 per cent and remains significantly different from zero. In Column 3, once the standardized scores on cognitive tests are added, the gender wage gap remains virtually unchanged at about 7.5 per cent. The reading score is positively and significantly linked with wages, but the numeracy score is not. While Glewwe et al. (2017) find that reading skills are not significant when one controls for educational attainment, in our case we find reading proficiency to matter even in the presence of educational attainment, indicating that the two variables measure different aspects of educational accumulation. In Column 4, we further add the standardized scores of the personality traits, which leads to a slight drop in the gender gap to seven per cent. The personality traits are neither independently nor jointly significant, suggesting that there is no incremental effect of these traits on mean wages. In Columns 5–8, upon augmenting each of these regressions by adding the firm dummies, we find that, within the same firm, the raw gender wage gap amounts to 11.3 per cent (Column 5) and 5.6 per cent (Column 6); once cognitive and socio-emotional skills are controlled for, the gender wage gaps amount to 4.7 per cent, but they are no longer significant. Reading score and numeracy score are positively correlated with wages in the presence of firm dummies (Columns 7 and 8). This indicates the existence of gender-based sorting across firms such that males are sorted into high-paying firms while females tend to be sorted into low-paying firms. The joint significance of the firm dummy variables further highlights that wages are correlated with firm-specific factors and that accounting for them is crucial. Tests indicate that reading and numeracy skills are always jointly significant in determining mean wages, while personality traits do not matter for pooled mean wages (see bottom of Table 3).

¹⁶ Söderbom et al. (2006) provide a discussion of whether the control function method can also address sample selectivity issues. Their answer is yes, provided the instruments are independent of the error term of the selected samples. We make a similar assumption here, i.e. that the cognitive skills and personality traits—a substitute for the control function approach—may be independent of the error term of the selected samples.

Table 3: OLS regressions of log current hourly wages

	Without firm-specific effects				With firm-specific effects			
	1	2	3	4	5	6	7	8
Male	0.116** (0.051)	0.073** (0.030)	0.075** (0.030)	0.070** (0.029)	0.113*** (0.042)	0.056* (0.030)	0.047 (0.029)	0.047 (0.029)
Married		0.063** (0.029)	0.064** (0.029)	0.063** (0.029)		0.038 (0.028)	0.039 (0.027)	0.038 (0.027)
Junior secondary		0.151*** (0.036)	0.119*** (0.038)	0.117*** (0.037)		0.137*** (0.038)	0.068 (0.041)	0.068 (0.042)
Secondary		0.353*** (0.044)	0.299*** (0.053)	0.297*** (0.052)		0.287*** (0.046)	0.170*** (0.053)	0.169*** (0.054)
Higher secondary		0.570*** (0.051)	0.501*** (0.064)	0.499*** (0.063)		0.536*** (0.055)	0.389*** (0.056)	0.387*** (0.056)
Post-secondary		1.013*** (0.050)	0.933*** (0.069)	0.925*** (0.067)		0.979*** (0.055)	0.819*** (0.057)	0.816*** (0.058)
Tenure		0.033*** (0.006)	0.032*** (0.006)	0.032*** (0.006)		0.039*** (0.006)	0.038*** (0.006)	0.039*** (0.006)
Tenure squared/100		-0.055** (0.024)	-0.054** (0.024)	-0.052** (0.024)		-0.069*** (0.022)	-0.067*** (0.022)	-0.069*** (0.022)
Prior experience		0.014 (0.016)	0.014 (0.016)	0.013 (0.016)		0.012 (0.016)	0.011 (0.016)	0.011 (0.016)
Prior experience squared/100		0.062 (0.077)	0.062 (0.078)	0.067 (0.077)		0.078 (0.074)	0.086 (0.074)	0.084 (0.073)
Reading score			0.051** (0.021)	0.054** (0.021)			0.060*** (0.022)	0.062*** (0.022)
Numeracy score			-0.019	-0.017			0.037*	0.036*

			(0.020)	(0.020)			(0.020)	(0.020)
Openness to experience				0.003				-0.003
				(0.015)				(0.014)
Conscientiousness				0.006				-0.002
				(0.013)				(0.015)
Extroversion				0.005				-0.010
				(0.013)				(0.012)
Agreeableness				0.007				0.020
				(0.017)				(0.013)
Emotional stability				0.002				0.004
				(0.013)				(0.011)
Hostile bias				-0.003				0.001
				(0.012)				(0.012)
Decision-making				-0.025				-0.007
				(0.015)				(0.013)
Constant	3.602***	2.910***	2.958***	2.970***	3.604***	2.950***	3.063***	3.061***
	(0.053)	(0.063)	(0.071)	(0.068)	(0.034)	(0.060)	(0.056)	(0.055)
Observations	2,150	2,150	2,150	2,150	2,150	2,150	2,150	2,150
R-squared	0.005	0.476	0.478	0.479	0.409	0.651	0.655	0.656
Firm effects	No	No	No	No	Yes	Yes	Yes	Yes
Joint sig. of cognitive skills (<i>p-value</i>)			0.054	0.038			0.002	0.001
Joint sig. of personality traits (<i>p-value</i>)				0.83				0.89

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

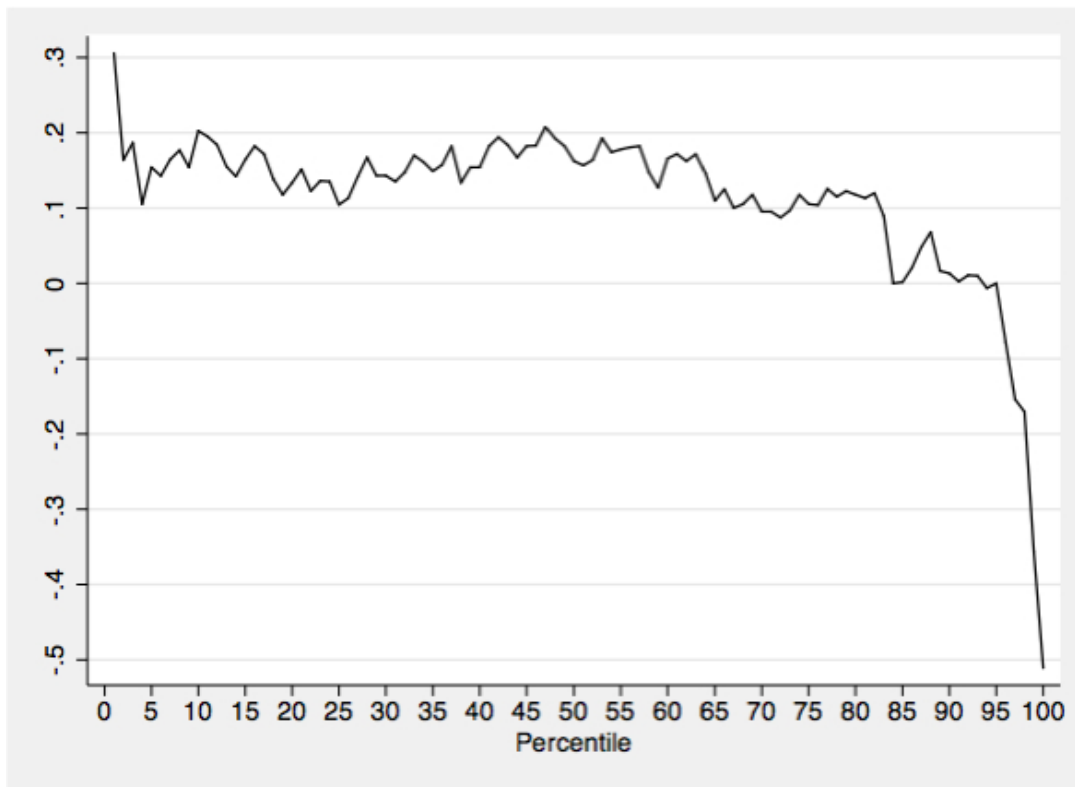
Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

In terms of other controls included in Table 3, we find that returns to education increase with the level of highest education completed. This is consistent with other evidence (e.g., Kingdon and Unni 2001; Söderbom et al. 2006). Tenure in current firm has the expected concave relationship with wages.

4.3 UQR

As can be seen in Figure 2, the magnitude of the unconditional gender wage gap (male minus female) varies throughout the wage distribution, with the highest gaps favouring males being observed at the lower percentiles, and the negative wage gaps (i.e. in favour of women) at the 95th percentiles and above.¹⁷ This phenomenon of greater wage gaps at the lower end is consistent with the ‘sticky floor’ phenomenon that has been observed in Bangladesh (Ahmed and Maitra 2015) and other developing countries (e.g., Carrillo et al. 2014).

Figure 2: Gender wage gap distribution



Note: Gender wage gap defined as male minus female wages.

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

We now estimate UQR 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. We pool the data for males and females in the quantile regression, on the assumption that the returns to endowments are the same at the various quantiles for men and women. Having established the salience of firm dummies in the OLS regressions, in Table 4 we estimate pooled UQR with firm-specific effects and report results at the 10th, 25th, 50th, 75th, and 90th percentiles. The gender wage gap is in the range of 7–11 per cent and significant across all the quantiles, but shows no clear increasing or decreasing trend once we control for all other factors.

¹⁷ There are sufficient males and females across the percentiles of the wage distribution. Further, males and females are similar at the top decile in terms of occupations.

The gap is eight per cent at the 10th percentile, slightly declines to seven per cent at the 25th percentile, further increases to 11 per cent at the median, declines to 6.5 per cent at the 75th percentile, and is finally 11 per cent at the 90th percentile. Both reading and numeracy scores have generally higher correlations with wages at the lower percentiles than at the higher (with the exception of the reading score at the 25th percentile). Among the personality traits, agreeableness seems to matter most, with this trait being positively associated with wages at the 25th, 75th, and 90th percentiles. Tests of joint significance indicate that while reading and numeracy tests are jointly significant at all points except the 90th percentile, the personality traits are only jointly significant at the 75th percentile.

In Table 5, we estimate gender-specific OLS and UQR with firm-specific effects. This allows us to relax the strong assumption that the returns to cognitive and socio-emotional skills and other covariates are the same across genders. The reading score is positively and significantly associated with female wages at all reported percentiles except the 10th. While it also significantly matters for male wages at some points, the association with reading skills is greater for female wages. In contrast, the numeracy score is positively and significantly correlated with male wages at all points except the 90th percentile, but is never significant for women. While in Table 4 we saw that the coefficients on reading and numeracy scores were positive and significant throughout most of the distribution, it is now evident that these results exhibit gender differentials. Considering the personality variables, we observe that agreeableness has positive and mostly increasing returns for women across the wage distribution. Conscientiousness is also rewarded for women at the mean and lower percentiles, while openness to experience is negatively associated with wages at the mean and at the top decile for women. For men, the effects of personality traits are more sporadic and reveal no consistent pattern. Tests reveal that personality traits are jointly significant at all percentiles for females, but this is not the case for men, indicating that personality traits are more important in determining women's wages than men's wages. Nyhus and Pons (2005), using Dutch data, also find that employers are more sensitive to personality differences among females than among males.

Our results of gender-specific UQR provide some support for the notion that the market rewards individuals who adhere to societal expectations about gender-appropriate traits and behaviour (Reuben et al. 2014). For instance, agreeableness may be a desirable trait in women, especially in a developing country such as Bangladesh where gender roles are deep-seated; women may be expected to be more submissive and accommodating in nature, both at home and in the workplace, and in our sample we find that more agreeable women are monetarily rewarded for this trait. However, this result contrasts with evidence from developed countries, where the trait of agreeableness is generally linked to lower wages, perhaps because agreeable individuals may be deemed 'too nice', cooperative, and reluctant to negotiate their wages (e.g., Grove et al. 2011; Mueller and Plug 2006; Nyhus and Pons 2005). The finding that numeracy is a skill rewarded for men, while literacy is rewarded more for women, is noteworthy, and reflects employers' internalized beliefs about men's and women's comparative advantages in numeracy and literacy skills respectively as well as an adherence to those stereotypes (Reuben et al. 2014). Societal beliefs about gender roles and the resulting internalization of such stereotypes by females have implications for women's under-representation in science, technology, engineering, and mathematics (Lavy and Sand 2015), and for gender gaps in maths and reading test scores (Guiso et al. 2008; Pope and Sydnor 2010).

Table 4: UQR of log current hourly wages (with firm-specific effects)

	1	2	3	4	5
	Q10	Q25	Q50	Q75	Q90
Male	0.083** (0.035)	0.070*** (0.027)	0.110*** (0.028)	0.065** (0.033)	0.108** (0.043)
Married	0.084** (0.042)	0.063** (0.030)	0.086*** (0.029)	0.065** (0.030)	-0.062* (0.037)
Junior secondary	0.136* (0.072)	0.176*** (0.046)	0.050 (0.037)	-0.067** (0.029)	-0.047 (0.031)
Secondary	0.183** (0.074)	0.376*** (0.050)	0.245*** (0.044)	-0.034 (0.040)	-0.030 (0.043)
Higher secondary	0.315*** (0.073)	0.586*** (0.052)	0.657*** (0.057)	0.072 (0.052)	0.017 (0.057)
Post-secondary	0.290*** (0.073)	0.639*** (0.051)	1.043*** (0.047)	1.118*** (0.062)	0.794*** (0.076)
Tenure	0.041*** (0.006)	0.044*** (0.005)	0.040*** (0.006)	0.034*** (0.007)	0.038*** (0.011)
Tenure squared/100	-0.115*** (0.022)	-0.115*** (0.019)	-0.074*** (0.023)	-0.024 (0.029)	-0.003 (0.043)
Prior experience	0.026*** (0.009)	0.010 (0.008)	0.021** (0.010)	0.020 (0.013)	0.027 (0.020)
Prior experience squared/100	-0.053 (0.032)	0.001 (0.032)	-0.016 (0.040)	0.019 (0.052)	0.099 (0.091)
Reading score	0.096*** (0.029)	0.020 (0.021)	0.059*** (0.022)	0.071*** (0.021)	0.036 (0.025)
Numeracy score	0.047** (0.022)	0.065*** (0.015)	0.040*** (0.014)	0.037** (0.015)	0.014 (0.021)
Openness to experience	-0.008 (0.017)	-0.017 (0.013)	-0.004 (0.012)	-0.004 (0.017)	-0.029 (0.022)
Conscientiousness	-0.004 (0.017)	0.017 (0.012)	-0.000 (0.012)	0.007 (0.015)	0.013 (0.020)
Extroversion	-0.026* (0.014)	-0.010 (0.011)	0.002 (0.012)	-0.016 (0.013)	-0.023 (0.018)

Agreeableness	0.017 (0.015)	0.030** (0.012)	0.008 (0.014)	0.059*** (0.017)	0.051** (0.021)
Emotional stability	0.024 (0.017)	-0.004 (0.011)	-0.010 (0.014)	-0.008 (0.017)	0.007 (0.022)
Hostile bias	0.021 (0.017)	0.011 (0.012)	-0.009 (0.013)	-0.033** (0.015)	-0.022 (0.020)
Decision-making	-0.022 (0.018)	-0.005 (0.013)	-0.006 (0.014)	0.010 (0.017)	0.008 (0.023)
Constant	2.515*** (0.075)	2.613*** (0.050)	2.764*** (0.048)	3.414*** (0.052)	3.852*** (0.070)
Observations	2,150	2,150	2,150	2,150	2,150
Joint sig. of cognitive skills (<i>p-value</i>)	<0.001	<0.001	<0.001	<0.001	0.18
Joint sig. of personality traits (<i>p-value</i>)	0.17	0.15	0.98	0.003	0.17

Notes: Dependent variable is log of current hourly wage. Bootstrapped standard errors based on 500 replications are reported in parentheses. *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

Table 5: Gender-specific OLS and UQR of log current hourly wages (with firm-specific effects)

	Males						Females					
	1 OLS	2 Q10	3 Q25	4 Q50	5 Q75	6 Q90	7 OLS	8 Q10	9 Q25	10 Q50	11 Q75	12 Q90
Reading score	0.034** (0.014)	0.095*** (0.030)	-0.001 (0.024)	0.037 (0.024)	0.044* (0.023)	0.026 (0.030)	0.149*** (0.028)	0.061 (0.065)	0.090* (0.049)	0.138*** (0.052)	0.195*** (0.051)	0.107** (0.054)
Numeracy score	0.045*** (0.010)	0.066** (0.026)	0.072*** (0.017)	0.041*** (0.015)	0.045** (0.018)	0.014 (0.025)	-0.011 (0.021)	-0.028 (0.056)	0.050 (0.034)	0.034 (0.034)	-0.004 (0.035)	0.010 (0.040)
Openness to experience	-0.007 (0.010)	-0.011 (0.018)	-0.025* (0.014)	-0.012 (0.015)	-0.006 (0.019)	-0.013 (0.026)	-0.038* (0.021)	-0.008 (0.036)	-0.003 (0.026)	0.023 (0.034)	-0.007 (0.036)	-0.116** (0.047)
Conscientiousness	-0.005 (0.009)	-0.020 (0.018)	-0.001 (0.015)	-0.006 (0.014)	0.007 (0.017)	0.009 (0.026)	0.042*** (0.016)	0.056 (0.036)	0.067** (0.027)	0.014 (0.025)	-0.001 (0.032)	0.023 (0.041)

Extroversion	-0.008 (0.008)	-0.025 (0.016)	-0.014 (0.012)	-0.001 (0.013)	-0.010 (0.016)	-0.025 (0.021)	-0.018 (0.015)	-0.030 (0.035)	0.017 (0.023)	0.015 (0.025)	-0.037 (0.032)	-0.002 (0.041)
Agreeableness	0.009 (0.010)	-0.001 (0.020)	0.015 (0.015)	-0.006 (0.016)	0.036* (0.020)	0.026 (0.025)	0.108*** (0.018)	0.088*** (0.032)	0.100*** (0.028)	0.062* (0.032)	0.143*** (0.037)	0.161*** (0.042)
Emotional stability	0.002 (0.010)	0.044** (0.020)	0.007 (0.014)	-0.015 (0.015)	-0.016 (0.019)	-0.001 (0.024)	-0.016 (0.017)	-0.059* (0.033)	-0.049** (0.022)	0.009 (0.031)	0.025 (0.034)	0.039 (0.044)
Hostile bias	-0.002 (0.009)	0.015 (0.018)	0.006 (0.014)	-0.003 (0.015)	-0.027 (0.018)	-0.015 (0.025)	-0.004 (0.018)	0.040 (0.040)	0.037 (0.026)	-0.046 (0.028)	-0.076** (0.035)	-0.052 (0.052)
Decision-making	-0.009 (0.010)	-0.029 (0.020)	-0.005 (0.014)	-0.007 (0.016)	0.001 (0.018)	-0.006 (0.028)	0.018 (0.019)	0.012 (0.038)	-0.009 (0.028)	0.005 (0.039)	0.046 (0.040)	0.058 (0.040)
Constant	3.101*** (0.034)	2.636*** (0.085)	2.658*** (0.060)	2.846*** (0.060)	3.444*** (0.074)	3.962*** (0.077)	3.083*** (0.067)	2.259*** (0.190)	2.686*** (0.116)	2.870*** (0.135)	3.584*** (0.138)	3.925*** (0.141)
Observations	1,730	1,730	1,730	1,730	1,730	1,730	420	420	420	420	420	420
Joint sig. of cognitive skills (<i>p-value</i>)	<0.001	<0.001	<0.001	0.001	0.003	0.44	<0.001	0.61	0.009	0.004	<0.001	0.08
Joint sig. of personality traits (<i>p-value</i>)	0.79	0.09	0.58	0.81	0.46	0.85	<0.001	0.007	<0.001	0.10	0.001	<0.001

Notes: Dependent variable is log of current hourly wage. Bootstrapped standard errors based on 500 replications are reported in parentheses. Controls include: married, education dummies, prior experience, prior experience squared, tenure, and tenure squared. *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

4.4 Decomposition analysis

In Table 6, we report results from the decompositions of the wage gaps. We first present the results of the mean Blinder-Oaxaca decomposition. We find that approximately 59 per cent of the wage gap is explained by our vector of right-hand side characteristics, with the remaining 41 per cent being unexplained. As mentioned in Section 2, an advantage of the RIF-based decomposition of quantile wage gaps is that it allows us to conduct a detailed decomposition wherein we can assess the contribution of each covariate to the explained and unexplained gaps. In general, we find the explained share to vary between 33 and 43 per cent at the various quantiles, with no clear increasing or decreasing trend. Therefore, a larger share of the gender wage gap remains unexplained.

Table 6: Detailed decomposition of quantile wage gaps (with firm-specific effects)

	1	2	3	4	5	6
	Mean	Q10	Q25	Q50	Q75	Q90
Total gap	0.116	0.136	0.122	0.162	0.11	0.163
Unexplained gap	0.047 (40.9)	0.083 (61)	0.069 (56.6)	0.109 (67.3)	0.065 (59.1)	0.108 (66.3)
Explained gap	0.069 (59.1)	0.053 (39)	0.053 (43.4)	0.053 (32.7)	0.045 (40.9)	0.055 (33.7)
Gap explained by:						
Tenure	0.03	0.015	0.017	0.02	0.023	0.03
Cognitive skills	0.012	0.017	0.014	0.013	0.013	0.006
Reading score	0.005	0.008	0.002	0.005	0.006	0.003
Numeracy score	0.007	0.009	0.012	0.008	0.007	0.003
Socio-emotional skills	0.0003	0.004	0.000	0.000	-0.002	0.004
Openness to experience	0.001	0.001	0.003	0.001	0.001	0.005
Conscientiousness	-0.000	-0.000	0.001	-0.000	0.000	0.001
Extroversion	0.000	0.001	0.000	-0.000	0.000	0.001
Agreeableness	-0.002	-0.002	-0.003	-0.001	-0.006	-0.005
Emotional stability	0.001	0.004	-0.001	-0.001	0.001	0.001
Hostile bias	-0.000	-0.003	-0.002	0.001	0.005	0.003
Decision-making	0.001	0.004	0.001	0.001	-0.002	-0.001

Note: Values in parentheses are the percentages unexplained and explained. They sum to 100 in each column.

Source: authors' calculations using 2012 Bangladesh Enterprise Skills Survey.

The lower panel of Table 6 presents the contribution to the explained gap of the key covariates of interest (cognitive and socio-emotional skills). Among other socio-economic characteristics, we report the contribution of the tenure or years of employment in the current firm, as that accounts for a large share of the explained gap throughout the distribution, in the range of 28–55 per cent. Combining reading and numeracy scores, we find that these measures of cognitive attainment together account for 17 per cent of the explained gap (0.012 out of 0.068 log points) at the mean. Among the quantiles, the gap explained by cognitive skills is larger at the lower end, and varies between 32 per cent at the 10th percentile and 11 per cent at the 90th percentile. A visual examination of the reading and numeracy scores separately shows that numeracy scores account for a slightly larger share of the explained component throughout the distribution (except the 90th percentile, where the magnitudes are identical).

Considering socio-emotional skills cumulatively, we find the magnitude to be relatively modest and tending to zero at the 25th and 50th percentiles. On the other hand, at the 10th and 90th percentiles, personality traits account for about seven per cent of the explained gap. Examining trait-specific magnitudes, we see that agreeableness makes a negative contribution, thereby reducing the total gender wage gap. This is because females score higher on agreeableness than males (see Table 2), and we also document greater returns to females for this trait (see Table 5).

Overall, consistent with the mean and quantile regressions presented in earlier tables, we find that cognitive skills have a greater explanatory power in accounting for the gender wage gap as compared with personality traits. However, labour market characteristics such as tenure in the current firm clearly account for a larger share of the wage gap throughout the distribution. Further, to the extent that the unexplained gap is indicative of gender wage discrimination, controlling for previously unmeasured cognitive and socio-emotional skills gets us to a closer approximation of actual wage discrimination.

5 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 socio-emotional skills as determinants of wages, over and above variables traditionally used in such analyses. We believe this makes an important contribution, especially when existing literature and available data on these issues are scarce for developing countries.

Our results show that while cognitive attainment as measured by reading ability is positively correlated with wages, measures of personality seem to have almost no explanatory power in determining mean wages for the gender-pooled sample. When 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 is gender-differentiated, such that reading and numeracy skills seem to confer benefits on women and men respectively. Further, the decompositions show that about 30–40 per cent of the wage gap can be explained by characteristics along the wage distribution. In line with regression analyses, we find that cognitive skills account for a larger share of the wage gap at the lower percentiles, and cumulatively account for a larger share of the composition effect than personality traits. However, the largest share of the composition effect is driven by one's length of employment in one's current firm.

The outlook of employers in our sample also lends support to the finding that cognitive skills and socio-economic characteristics are more important than personality traits in determining wages. In the survey, employers are asked to rate the importance of the following criteria on a 1–10 scale when making hiring decisions (10 being very important): academic performance, work experience, job skills, and interview. Sixty-eight per cent, 57 per cent, and 50 per cent of employers rate academic performance, work experience, and job skills respectively at 8–10. On the other hand, only 36 per cent of employers consider the interview to be an important criterion. This suggests that employers place greater consideration on observables rather than on face-to-face interactions during interviews, which give them a chance to assess the applicants' assertiveness, agreeableness, communication skills, etc. This could also point to generally low levels of learning and cognition in countries such as Bangladesh, which might explain employers' emphasis on evaluating those skills.

To the extent that gender wage gaps can be explained by gender gaps in skills and traits, a natural policy implication would be to consider ways in which the gender gap in skills could be mitigated. While a part of skill formation is genetic, recent evidence shows that these skills and traits can be shaped through education and other tailored interventions starting from a young age (e.g., Heckman et al. 2013; Kassenboehmer et al. 2018). However, societal gender stereotypes continue to prevail wherein similarly qualified males and females are perceived differently. Internalization of such gendered expectations and stereotypes by women has the potential to undermine the investments they make in themselves, thereby leading to a persistent gender-based skills gap. How and why such stereotypes about gender roles persist and lead to gender inequality in labour markets in Bangladesh, and in developing countries more generally, would be worth investigating further.

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