Cognitive and non-cognitive skills, hiring channels and wages in Bangladesh

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Abstract

This paper uses a novel matched employer-employee data set from Bangladesh, representing the formal sector, to estimate the relative importance of non-cognitive skills and the interplay between skills and hiring channels in determining wages. Our estimates of returns to schooling are positive and convex. Cognitive skills (literacy) affect wages only by enabling workers to use formal hiring channels. Wage returns to non-cognitive skills (extraversion) are positive and significant, however, only for those who found their job through formal hiring channels. We further find heterogeneous returns by occupation and educational level. Firm characteristics can help explain part of the differential returns to skills by hiring skills: employers who value team-work are associated with a smaller wage gap between workers who found their job through formal hiring channels and those who found their job through social networks.

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1 Introduction

Human capital has long been recognized as a predictor of wages and other labor market outcomes. While the literature has traditionally focused on the effect of classical human capital components such as education and experience on the labor market, non-cognitive skills like persistence, motivation, and communication have more recently been found to have an effect on wages and labor market outcomes beyond cognitive ability.

Non-cognitive skills are likely to have both a direct and indirect effect on wages. The direct effect stems from personality being considered as part of a worker's endowment. The indirect effect comes from personality affecting, for instance, occupational choice (Cobb-Clark and Tan, 2011), educational attainment (Heckman et al., 2006), or job search methods (Caliendo et al., 2014). Literature so far has focused on developed countries and oftentimes on either direct or indirect effects. Little research has been done regarding wage returns to non-cognitive skills in developing countries, which are likely to be different. For instance, employers in developing countries might reward skills that deal more with the precise execution of tasks (such as being conscientious and emotionally stable) instead of skills that deal with intellectual curiosity and independent working (such as openness to experience or extraversion).

We use a novel matched employer-employee data set from Bangladesh to estimate wage returns to non-cognitive skills while taking into account one important feature of the labor market in developing countries — the choice of hiring channel. We thus consider both the direct and indirect effects of cognitive and non-cognitive skills on wages. The cognitive skills included are numeracy and literacy tests; the non-cognitive skills considered are the Big Five personality test (openness to experience, conscientiousness, extaversion, agreeableness, and emotional stability) and a set of socio-emotional skills (hostile attribution bias and grit). Additionally, we explore demand-side preferences for specific skills by decomposing within-firms wags gaps between workers who have been hired through formal channels and those who have been hired through networks to better understand whether those gaps are driven by firm characteristics and preferences for specific skills.

The survey covers the formal sector which is the sector that will contribute strongly to the shift from agriculture into higher skilled sectors. While most of Bangladeshi employment still occurs in the informal sector, three quarters of new jobs over the last ten years were added in the more formal, non-agricultural sector (World Bank, 2015). The paper hence contributes to a better understanding of which skills are required in the part of the labor market that will likely be the driver of faster GDP growth and poverty reduction.

We find that reading skills have a positive effect on male mean wages, even when controlling for educational attainment. However, the effect of literacy is purely indirect: literacy affects wages through increasing the probability to choose formal hiring channels over others. Once this initial selection has been corrected for, there is no further significant wage return to cognitive skills. Non-cognitive skills also affect the selection of the hiring channel: higher agreeableness, conscientiousness, and a lower hostile attribution bias are associated with a higher probability of having been hired through family, friends, and village connections or political and school alumni associations, respectively. Non-cognitive skills further have a direct effect on wages, after correcting for initial selection. For those hired formally, a one standard deviation increase in extraversion is associated with a 3 percent increase in wages, which is considerable if compared to average returns to education in developing countries. Focusing on the demand side to understand whether firm characteristics can help explain the differential returns to skills, we find that employers who value interviews are associated with a smaller within-firm wage gap between workers hired through different channels, while those who value communication skills and formal education exhibit a larger within-firm wage gap.

The remainder of this paper is organized as follows: section 2 provides an overview of the literature and lays out our conceptual framework, section 3 introduces the data, section 4 describes the methodology used, section 5 presents main results, and section 6 concludes.

2 Literature and conceptual framework

2.1 Literature review

The impact of education and experience on wages has been a widely discussed phenomenon since Becker (1964) and Mincer (1974).[1] However, focusing on returns to education ignores the innate multidimensionality of human capital, which also comprises cognitive ability and non-cognitive skills. While literature recognized the potentially important role cognitive and non-cognitives could play on the labor market, lack of data meant that oftentimes they were part of the unobservables.

Cognitive skills have often been approximated via standardized test scores in developed countries and literacy as well as numeracy tests in developing countries. Hanushek and Woessmann (2008) provides evidence that it is the possession of cognitive skills rather than mere school attainment that is most powerfully related to individual earnings, and that average years of education becomes insignificant once test scores are included as an additional control variable. While most of the literature has focused on the United States, similar results have been found for other developed countries. Hanushek et al. (2015) use a cross-country data set for OECD countries and find that returns to cognitive skills (numeracy and literacy) are considerable but on average smaller than in the US. However, assessing the differential impacts of years of schooling and cognitive skills on labor market outcomes is not without problems, since including intelligence test as control variables for ability could worsen rather than improve their inherent bias, as these tests are themselves subject to measurement error (Griliches, 1977). Cawley et al.

[1]Psacharopoulos and Patrinos (2004) provide a global overview and estimate that the average rate of return to another year of schooling is about 10 percent.

(2001) illustrates this difficultly: using the US National Longitudinal Survey of Youth (NLSY), they find that cognitive ability and schooling are so highly correlated that their effects on wages cannot be estimated without imposing strong parametric structures on any estimation.

Non-cognitive skills like personality traits and behaviors have recently been included in the analysis of labor market outcomes. Being able to learn, to lead, to communicate, to work in a team, or to deliver results in a timely manner might in the end be as important as cognitive ability. Indeed, non-cognitive skills have been found to be strongly associated with higher earnings, to have a positive effect on wages beyond the effect of pure cognitive ability (Heckman et al., 2006), and to be a predictor of labor market outcomes and wages (Heineck and Anger, 2010; Borghans et al., 2008). Mueller and Plug (2006) show that the effect of personality traits on earnings is of similar magnitude to that of cognitive skills. Still, the relative importance of various personality traits differs. In the Big Five personality traits model, conscientiousness has been shown to be associated positively with job performance (Nyhus and Pons, 2005) and to determine performance and wages alongside traits related to emotional stability (Drago, 2011). Recently, "grit", the perseverance for long term goals, has taken a prominent place in predicting success in several settings, such as educational attainment and grade point average (Duckworth et al., 2007), suggesting that such perseverance might be more, or at least as important, as actual talent. Still, Lindqvist and Vestman (2011) argue that while lack of non-cognitive skills is a strong predictor of bad labor market outcomes (such as unemployment or low annual earnings), cognitive rather than non-cognitive skills determine wages. Similarly, OECD (2015) suggests that raising cognitive skills might ultimately be more important than raising socio-emotional skills in determining incomes.

Research on returns to non-cognitive skills has largely focused on developed countries, with a few notable exceptions. Blom and Saeki (2011) find evidence that employers of engineers in India stress interpersonal skills such as reliability and willingness to learn above cognitive skills such as literacy and numeracy. In Peru, Díaz et al. (2013) find that returns to perseverance are as high as returns to average cognitive ability. Acosta et al. (2015) find that in Columbia, cognitive skills predict higher earnings and better labor market outcomes (such as holding a formal sector job) and non-cognitive skills affect participation in the labor market.

The previous paragraphs have demonstrated that personality traits have not only a direct, but also an indirect impact on wages by determining, for instance, labor market participation or formality status. In this paper, we are focusing on one indirect factor which is very prevalent in developing countries, namely the use of social networks in the hiring process. If individuals self-select into different channels of job search depending on (among other things) their human capital, the hiring channel could then mitigate the wage returns of skills. This is particularly important in developing countries, where formal institutions are traditionally weak and social networks are employed frequently for job search (Fafchamps, 2006). In theory, social networks have been found to both increase and decrease wages.

On the supply side, informal networks are understood to be preferred by workers because they are less expensive and characterized by a higher probability of finding a job (Holzer, 1988). On the demand side, the use of social networks has traditionally been justified by mitigating selection problems through reduced asymmetric information between employers and employees and improved matching (Montgomery, 1991; Simon and Warner, 1992). In these models, current employees possess information about unobserved characteristics of applicants or the match quality. Jobs obtained via social networks should then result in higher wages. Having to use social networks to find a job can also be perceived as a negative signal to employers, however, as those relying on networks might simply be workers in greater need of a job of any sort (Granovetter, 1995). If the latter channel is at work, workers searching for jobs via social networks exhibit a lower reservation wage, suggesting that finding a job through a social network will thus be negatively related to wages. Most of the models in the network literature assume exogenous network formation and homogeneity of workers and firms. Taking into account endogenous network formation (particularly concerning the size of a network) and heterogeneity of workers and firms can lead to ambiguous prediction of network hiring on wages (Beaman, 2015). Empirical results are equally mixed, with some studies supporting a positive relationship between social network job searches and wages (e.g. Kugler, 2003; Simon and Warner, 1992) while others suggest a negative one (e.g. Bentolila et al., 2010; Berardi, 2013).

In practice, heterogeneous workers and firms as well as endogenous network formation are quite likely. For instance, human capital affects job search differently for different types of workers and also influences network formation. Social networks tend to be used predominantly by less educated workers of a lower socio-economic status (Topa, 2011). In terms of cognitive skills, Lee et al. (2014) suggest that individuals with higher cognitive skills have access to broader social networks and are better able to signal their productivity through their social network. Individuals who possess more of certain non-cognitive skills (openness to experience, extraversion and emotional stability) further have access to larger and more diverse social networks (Wu et al., 2008; Pollet et al., 2011). Caliendo et al. (2014) show that non-cognitive skills also play a role in influencing job search; the authors find that individuals with an internal locus of control exert higher search effort.

2.2 Conceptual Framework

The literature reviewed illustrates that cognitive and non-cognitive skills are likely to have a direct and an indirect effect on wages. The direct effects stems from personality being considered as part of a worker's endowment, which is being rewarded directly by the employer if the endowment matches the requirements for the job. The indirect effect stems from cognitive skills and personality affecting channels that lead to a job such as occupational choice (Cobb-Clark and Tan, 2011), educational attainment (Heckman et al., 2006), or job search methods (Caliendo et al., 2014). In the case of hiring channels cognitive skills and non-cognitive skills have an indirect effect on wages assuming that jobs available or remuneration for the same job, differ by hiring channel. For instance, formal hiring channels, such as newspaper ads, might publicize mostly white-collar, well-paid office jobs, while blue-collar jobs requiring heavy manual labor are rather available through word of mouth, transmitted by friends and family.

So far, literature has either focused on the wage returns to cognitive and non-cognitive skills in developing countries (the direct effect), or on the effect of cognitive and non-cognitive skills on mitigating factors, such as job search methods (the indirect effect). To our knowledge, no paper has so far considered both the direct and indirect effect of cognitive and non-cognitive skills on wages. This paper does both, by first looking at the effect of cognitive and non-cognitive skills on hiring channels chosen and then estimating outcomes of the job search, i.e. returns to wages for those skills, given the initial selection into hiring channels. Figure 1 illustrates the underlying conceptual framework. Human capital does in our case not act as an instrumental variable but is assumed to have also a direct effect on wages, above and beyond the effect it has on the hiring channel.

To illustrate the conceptual framework, assume that a worker is very agreeable. Individuals who score high on the personality trait agreeableness are usually considerate, generous, and willing to compromise their interest with others. An agreeable person is likely to have a larger and closer group of friends. Thus, we assume that scoring higher on the character trait agreeableness increases a worker's probability to find a job through friends or other social connections. However, agreeable individuals are likely to compromise their interest with others, which is not necessarily something that is valued in the work-setting. Hence, the trait agreeableness could have an indirect effect on wages through enabling network hiring, but no direct effect on wages.

Looking at the indirect effects, we expect education to have a positive effect on formal hiring, as the network channel has been found to be used more often by workers with a lower socio-economic status (Topa, 2011). Similarly, we expect cognitive skills to have a positive effect on the probability to have found the job through formal channels. Conscientiousness has been linked to being a hard worker and exhibit strong self control. It is likely that such a worker would find work more easily through social networks who would be more willing to provide a recommendation. We expect a similar effect from emotional stability, which has been linked to better task performance. People who are more extroverted, more outgoing and taking on leadership roles, have access to a larger social network and might hence receive more information and offers through the network, increasing their likelihood to find a job through the network. As mentioned in the example above, we assume agreeableness to have a positive effect on network hiring. Grit refers to persistence in actions. As social networks often provide the quicker option to find a job we assume that people who score higher on the grit scale continue their formal job search until they find a job. Grit would then have a negative effect on the probability to find a job through networks. Workers who score higher on the hostile attribution bias are assumed to be less likely to find a job through networks. Hostile attribution bias is a cognitive bias which leads to individuals interpreting other's behavior as hostile towards oneself, leading to them not searching for work through (potentially hostile) social connections. The effect of openness to experience remains a priori unclear.

Considering the direct effects, we expect our estimates for wage returns to education to be positive and potentially non-linear, and our estimates for the returns to cognitive skills be positive and significant. Literature on wage returns to non-cognitive in developing countries is scarce. In developed countries, the literature has found positive effects of the Big Five traits conscientiousness, extraversion, emotional stability, and grit on career success (Judge et al., 1999; Duckworth et al., 2007). Conscientiousness and grit quite naturally coincide with professional success. Extraversion is a trait that can be especially useful in a business environment, while emotional stability enables performance on specific tasks. Hostile attribution bias is assumed to have a negative effect on wages. The effect of the remaining two Big Five personality traits on wages is less clear. Openness to experience is related to flexibility, creativeness, and intellectual orientation, which could have a positive effect on wages. At the same time, openness to experience has also been linked to more autonomy and non-conformity, which might not necessarily be rewarded on the labor market. Similarly, agreeableness coincides with being more likable and cooperative, which can be very beneficial in a team work setting, but might be a hindrance if the worker places his co-workers interests above his own.

3 Data

This study is based on the 2012 Bangladesh Enterprise-Based Skills Survey (ESS), a matched employer-employee survey commissioned by the World Bank with the aim to assess whether the educational system in Bangladesh is producing graduates with skills relevant to and demanded by firms (Nomura et al., 2013).[2] The survey covers formal sector firms in the industrial and manufacturing sectors. Most of Bangladeshi employment occurs in the informal sector, however, the formal sector is expected to strongly contribute to the shift from agriculture into higher skilled sectors.

The survey covers firms in five industries: manufacturing, commerce, finance, education, and public administration. In total, the sample contains 500 firms and 6,981 individuals, stratified by economic sector and firm size: small (less than 20 employees), medium (21-70), and large (71+). Despite being limited to these five sectors, the survey is quite representative of employment in the Bangladeshi formal sector, as these sectors cover 87 percent of formal sector enterprises and 91 percent of total formal sector employment in Bangladesh (Nomura et al., 2013). The survey unit of the ESS is the firm; the survey consists of two modules, one each for employers and employees. Responses for the employer module come from business owners and high-level managers; its questions deal with information on recruitment and training of employees, as well as an assessment

[2]The authors were part of the team designing and conducting the survey.

of the workplace and firm performance.

The employee part of the survey is conducted for a sub-sample of employees in the sampled firms.[3] It contains detailed information of each individual's educational background and numeracy and literacy skills measured by an objective test, as well as a personality self-assessment. The employee survey also asks workers how they found their current job. Formal channels include media advertising, school placement, public and private employment services, job fairs, and internet posting. Social network channels include family or relatives, friends, through village connections, or through political and school associations.

Measures for numeracy and literacy stem from questions of the National Student Assessment conducted by the Bangladeshi Department of Primary Education (Nomura et al., 2013), designed to assess skills that workers who have completed primary school should possess. This test is administered to all workers, regardless of whether or not they have completed primary education. Personality measures included in the wage regressions are based on the Big Five typology of personality tests. The Big Five are a widely used list of key traits, which are understood to capture the broadest level of personality traits (McCrae and Costa, 2008).[4] The Big Five framework includes: (1) openness to experience, close to pure intellect, this trait is capturing one's tendency to be open to new experiences (aesthetic, cultural or intellectual); (2) conscientiousness describes one's tendency to be organized, hardworking, responsible; (3) extraversion encompasses directing one's interest towards the outer world of people and things; (4) agreeableness is the tendency to act cooperatively and in an unselfish manner; and (5) emotional stability is the predictability and consistency in emotional reactions with absence of rapid mood changes. The short Big Five Inventory (BFI-S) was included in the survey. This shortened version was originally developed by John and Srivastava (1999) and has been validated in large panel survey such as the German Socio-Economic Panel Survey. The survey further includes the socio-emotional skills grit and hostile attribution bias. Grit is the tendency to sustain interest in long term goals and persistence. Hostile attribution bias refers to a cognitive bias which leads to individuals interpreting other's ambiguous behavior as hostile towards them.

The employer part of the survey was answered by senior management. It contains information on senior management itself (such as gender, education), the firm's preferred hiring channels, the importance of certain selection criteria for hiring potential employees (such as academic performance, skills, or affiliation with an informal network), whether the company has formal performance reviews for its workers, and the importance that it places on types of skills in its workforce (such as team working, problem solving or

[3]Every 3^{rd} person in a small firm; every 5^{th} and 7^{th} person in a medium and large firm; and if employment exceeds 200, every 30^{th} person is interviewed (Nomura et al., 2013).

[4]The Big Five factor model is usually attributed to Allport and Odbert (1936) who theorized that important human individual differences are encoded in language. Allport and Odbert used personality describing words from English dictionaries, which they condensed into five broad factors using factor analysis. The Big Five taxonomy has since been replicated across cultures (John and Srivastava, 1999) and developmental stages of the life course (Soto et al., 2008).

motivation).[5]

4 Methodology

Our methodological approach consists of estimating different models to evaluate the impact of cognitive and non-cognitive skills on wages. We restrict our sample to male workers who have non-missing skills variables, since men and women might differ in non-cognitive skills (Fortin, 2008) or the same personality trait might be valued differently by employers (Heineck and Anger, 2010). Nordman et al. (2015) find personality traits reduce the male-female wage gap in the upper part of the wage distribution using the same data set as this paper.

We start from Mincer-type wage regressions and take into the account the indirect effect of the use of networks through bimodial and multinomial switching models. We then move to the demand side to look at firm-level determinants of the wage gap between formal and network hires. We decompose the observed within-firm wage gap between workers hired formally and through networks to understand whether is it driven by firm characteristics.

4.1 Returns to skills

Our basic model is a simple Mincer specification:

$$lnw_{ij} = \beta_0 + \beta_1 A_i + \beta_2 Cog_i + \beta_3 NonCog_i + \beta_4 B_j + \epsilon_{ij} \tag{1}$$

where lnw_{ij} is the natural logarithm of the hourly current wage for individual i in firm j. A is a vector of worker i's demographic characteristics including years of formal education, his time spent at the current firm (also including a squared term), previous work experience and a dummy for being married. Returns to education especially in developing countries are likely to be non-linear (Söderbom et al., 2006; Kuepie et al., 2009), which we capture with a simplified model using a low-order polynomial (Card, 1999). We further introduce controls for occupation, since Heckman et al. (2006) have shown that individuals sort into occupations and education based on their personality so our estimate of returns to personality could be overestimated if it only captures occupational effects. Cog further includes individual i's cognitive skills, the standardized score of the individual on numeracy and literacy tests, and $NonCog$ his non-cognitive skills, the standardized scores of each dimension of the Big Five personality assessment (openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability) and the standardized scores of the socio-emotional skills grit and hostile attribution bias. B is a vector of firm characteristics such as industry, firm size, the gender of top

[5] Nakata and Nomura (2015) use the same data set and analyze the decomposition of the wage gap between workers hired formally and through networks.

management and whether the firm exports; ϵ is the error term.[6] We control for firm characteristics to capture the effect that firm-level determinants of wages might have on wage setting (Groshen, 1991; Abowd et al., 1999).

All of our variables are measured at the same point in time (year 2012), after schooling has been completed and the worker has entered the labor market. If some of our control variables in the past influenced the degree to which others developed, our OLS estimates for returns to education or skills will be biased downwards, potentially underestimating the true effect. To illustrate, if cognitive ability is increased through education, by including controls for cognitive skills (literacy and numeracy) as well as educational attainment, our estimates for returns to cognitive skills would be lower than the true effect. Cognitive skills as well as non-cognitive skills have been shown to be malleable by the educational system but also to be predictors of educational attainment (Heckman et al., 2006).[7] Additionally, measurement error in for both, cognitive and non-cognitive skills is quite likely. Our estimates should therefore rather be interpreted as lower bounds.

In a second specification, we use starting wages instead of current wages as the dependent variable in the wage equations. Using starting wages has the advantage that starting wages are set before the employer is intimately familiar with the worker. It is thus interesting to see the effect especially of cognitive and non-cognitive skills on starting wages, since the only information the employer has at this point in time comes from the hiring channel (formal interviews, or information transmitted through social network) and observable information that we can control for, such as experience and educational attainment. It is thus very likely that the returns to these skills differ for starting wages even more so than for current wages. If we find significant returns to some variable for current, but not for starting wages, this suggests that these effects are not spurious but stem from the employer learning about the worker's productivity and match to their job.

Pairwise correlations between the different types of skills and personality traits show small correlations between the different personality traits, as well as between the personality traits and our cognitive variables (see Table A1 in the Appendix). In fact, our correlations are below those found by Cunha and Heckman (2008) who show correlations of 0.3 between cognitive and non-cognitive factors, whereas our highest correlation coefficient is of the order of 0.18. On the other hand, the correlation between cognitive factors and years of education attained is very large for the literacy test (0.75) and still quite substantial for numeracy (0.50); correlations between years of education

[6]We also estimate the model with firm fixed effects instead of firm characteristics. Results are similar but since estimations with firm-fixed effects rely on within firm variation, our sample size is smaller (3,133 male workers instead of 4,678). Since results are comparable we prefer to use firm characteristics.

[7]Almlund et al. (2011) discuss how using previously measured traits as predictors of later outcomes is problematic if the traits evolve over time. However, psychological research has demonstrated the stability of personality traits beginning in young adulthood Mischel and Shoda (2008) and economic research has recently shown that personality traits of working age Australian adults are stable over a four-year period (Cobb-Clark and Tan, 2011).

and the non-cognitive skills are small but have the expected signs (i.e. conscientiousness, grit and openness to experience all correlate positively with years of education attained).

4.2 Skills and the type of hiring channel

While OLS regressions provide a starting point, they confound the direct and indirect effects that cognitive and non-cognitive skills have on wages. They are not able to take into account that some unobserved characteristics that influence the choice of hiring channel could also influence the wages that the worker receives once employed. For example, less able or more extroverted workers might have a higher probability to find their job through networks such as friends and family. Once employed, the wage worker could then earn less due to his lower innate ability in performing his job, due to having been hired through networks, or a combination of the two. At the same time, the hiring channel might mitigate the impact of wage determinants, for example if employers have prejudices about the type of skills to expect in workers hired through different channel and reward those skills differentially. An endogenous switching model is able to correct for both the endogenous sample selection and the switching impact of wage determinants and has been used to investigate hiring channels in developed (Delattre and Sabatier, 2007) and developing countries (Berardi, 2013). We therefore estimate bimodial and multinomial endogenous switching models.

We start by noticing the two different states in which workers can find themselves, namely having been hired through formal channels or having been hired to their current job through networks. Each worker is only observed in one regime at a time.

$$lnw_{ij}^F = \beta_0^F + \beta_1^F A_i + \beta_2^F Cog_i + \beta_3^F NonCog_i + \beta_4^F B_j + \epsilon_{ij}^F \tag{2}$$

$$lnw_{ij}^N = \beta_0^N + \beta_1^N A_i + \beta_2^N Cog_i + \beta_3^N NonCog_i + \beta_4^N B_j + \epsilon_{ij}^N \tag{3}$$

where lnw_{ij}^F is the natural logarithm of the hourly wage rate of worker i, hired through formal channels, lnw_{ij}^N the natural logarithm of the hourly wage rate of worker i hired through networks, vectors A, Cog, and $NonCog$ are vectors of worker i's demographic characteristics, his cognitive and non-cognitive skills, respectively. B_j is a vector of firm j's characteristics, and ϵ_{ij}^F and ϵ_{ij}^N are the error terms for formal and network hires. We use the same worker and firm characteristics as in the OLS regressions in section 4.1.

The switching regression then sorts individuals in either of the two regimes. Choosing which channel to use when engaging in job search is not exogenous, but depends on the expected gains or losses associated with finding a job formally or through networks, given one's level of skills. Worker i therefore engages in job search through his social networks *(NET)* if:

$$NET_{ij}^* = \gamma Z_{ij} + u_{ij} > 0 \tag{4}$$

where Z_{ij} is a vector of explanatory variables for job search through social networks and u_{ij} an error term. NET_{ij}^* is unobserved. We do, however, observe whether or not the individual was actually hired through his networks and thereby whether or not he did use at least one of his potentially multiple channels of job search:

$$NET_{ij} = \begin{cases} 1 \text{ if } NET_{ij}^* > 0 \\ 0 \text{ if not} \end{cases} \tag{5}$$

The available data allow us to control for several observable characteristics at the worker and firm levels. Still, individuals choosing to engage in job search through networks and those choosing to use formal channels might differ in unobserved characteristics. We introduce *mother has no formal education* and *household size* as identifying variable to approximate the aspect of network quality and size of the (family) network which could influence its usage. Networks have long been thought to form among similar people (the 'homophily' principle) (Lazarsfeld and Merton, 1954; McPherson et al., 2001); at the same time, the size and diversity of the network ('strength of weak ties') is highly relevant for job search by linking individuals to information that is unavailable in their own circles (Granovetter, 1973). The relative importance of diversity versus similarity seems to depend on the current position of the individual in the social hierarchy (Lin, 1999). If a worker is in a lower social position, relying on weaker ties and reaching out vertically will put the individual in contact with people in a higher social position. If the individual is already in a high position, reaching out vertically does not provide the same benefit. The individual would then benefit more from searching among his own, stronger ties, by reaching out horizontally. By using the parent's formal educational attainment and the size of the family, we try to capture part of this quality and quantity element of social networks.[8]. The data allow us to control for an individual's education, his cognitive skills, and his personality. Since we are able to control for almost all of the genetic factors that could correlate between a mother and her child (except possibly genetic effects of height), we believe that the only way a mother's education could have an effect on her child's wages is through providing access to different types of social networks, thus satisfying the exclusion restriction.

We estimate the switching model using first a bimodial selection correction, distinguishing between workers hired formally or through social networks, and second a multinomial selection correction, allowing for five different hiring channels (formal, family, friends, village, and political or school alumni organizations). By modeling selection multinomially, we are able to investigate whether returns to skills vary by the type of social network used for successful job search and also whether personality types can help predict the probability of using one type of network versus another. The structure is similar to the bimodial endogenous switching model outlaid above; however instead of outcome equations (2) and (3), we now have five equations, one for each network

[8]We also tried specifications using the formal education of the father as well as identifying the model by its functional form (i.e. without exclusion restriction). We opted for the formal education of the mother, since father's education was not a good predictor of hiring channel choice and an exclusion restriction is generally the preferred option.

category. In the first stage, we used multinomial logit models to retrieve the correction terms which are based on the predicted probability of worker i to have found the job through one of the five hiring channels.[9] These correction terms, in effect generalized forms of the inverse Mill's ratios, are then added in a second step in the wage equations for each hiring channel and render consistent estimates of the effect of skills on wages, accounting for the selection into hiring channels. We rely on the selection correction developed in Bourguignon et al. (2007). The number of correction terms in this equation is then equal to the number of multinomial choices (5 choices in our case). The selection terms () can be interpreted to capture the direction of the selection bias between different sectors. For example, a positive ρ related to the friends hiring channel selection equation in the family hiring channel wage equation means that individuals enjoy higher wages if they have been hired through family compared to individuals taken at random, due the allocation of workers with worse unobserved skills out of hiring through family and into hiring through friends. *Mother has no formal education* and *household size* are again used as identifying variables which are included in the selection equation but can be legitimately excluded from the wage equations.

5 Results

5.1 Descriptive statistics

We restrict our sample to male workers who have non-missing non-cognitive skills variables. In total, we keep 4,678 male workers and 487 firms in our sample.[10] Table 1 presents descriptive statistics of the firms in our sample. A small number of firms (13 firms) is excluded from the analysis since they did not have male workers with non-missing skills variables. Table A7 illustrates that this does not significantly change our sample composition. The data include firms from five economics sectors: commerce (wholesale, retail), education, finance, manufacturing and public administration, with manufacturing representing a larger share of the sample due to the importance of this sector for the Bangladeshi economy. The majority of workplaces interviewed in the sectors commerce, education and finance are not part of a larger company, while firms in the manufacturing and public administration sectors typically belong to a larger company. Firms in the public administration sectors are almost all government organization, though the picture is more mixed in the education sector, which is comprised out of a mixture of government owned, autonomously owned and NGO owned companies.[11] The public sector companies include a variety of economic activities, ranging from agriculture to administrative

[9] We performed Hausman and Small-Hsio tests to make sure that the independence of irrelevant alternatives assumption (IIA) required for the multinomial logit model holds.

[10] By limiting our sample to men only, we lose about 12 percent of the original sample. Table A2 in the Appendix provides descriptive statistics of the original sample by sex.

[11] The school system in Bangladesh consists of a heterogeneous mix of education providers, including the government, secular private sector initiatives, religious authorities and NGOs (World Bank, 2013).

support and social work. Companies in the remaining sectors (commerce, finance, and manufacturing) are private enterprises or individually owned entities. Table 1 shows that the use of networks is extremely prevalent among firms: 33 percent of firms use social networks as their main channel of advertising job openings. For a little more than half of the sample (54 percent), social networks are at least one of their hiring channels.

Table 2 presents the characteristics of a random sample of employees within the firms. Most workers surveyed are on average 32 years old with about 5.5 years of work experience at their present job. On average, employees only had two years of experience prior to entering their current jobs, suggesting rather low job mobility. Most of the workers are skilled white or blue collar workers, which is due to the specific sample of firms (formal firms). The majority of workers are located in Dhaka, the capital. 31 percent of workers have at most primary education, 46 percent have completed secondary education and the remaining 23 percent have obtained tertiary education. Workers score worse on the literacy test than on the numeracy test, and score lowest on the personality trait hostile attribution bias, and highest on emotional stability. A slight majority of workers obtained their current job via networks (54 percent).

Comparing workers who found their job through formal job search methods and those who found their job through networks (the last two columns of Table 2) further reveals important differences between the two groups. Workers who found their job through formal channels earn on average higher wages, are slightly older, are more likely to work in skilled white collar occupations (76 percent vs. 38 percent), are less likely to live in Dhaka (51 percent vs. 65 percent), score higher on both numeracy and literacy tests, and are more educated (7 percent of the formal hires have obtained at most primary education vs. 50 percent of network hires). However, interestingly, looking at non-cognitive skills does not show any substantial differences between the two groups.[12]

5.2 Returns to skills

We estimate OLS regressions with the log of the current hourly wage as the dependent variable and a basic set of covariates that is gradually expanded. The first set of covariates consists of those commonly used in basic Mincer type regressions, explaining wages as a function of human capital (schooling in the original model) and experience. The covariates included are years of education, experience prior to joining the firm, time the individuals has spent working in the current firm (tenure), as well as quadratic effects for these three variables and a dummy variable for being married. We continue by including our measures of cognitive ability (standardized scores on numeracy and literacy tests) and non-cognitive skills (standardized values of the Big 5 personality test, and the socio-emotional traits hostile attribution bias and grit). Lastly, we include dummies for

[12]The survey does not contain information on whether workers within the firm are formal or informal workers. However, more than 90 percent of employment in formal firms in Bangladesh is formal employment (Asian Development Bank and Bangladesh Bureau of Statistics, 2012). We can hence assume that our results are indeed caused by differences in hiring channels and not in formality status.

occupations and firm characteristics. By including cognitive and non-cognitive skills as well as firm characteristics we can control for a large amount of otherwise unobserved worker and firm heterogeneity. Results are displayed in Table 3.

In accordance with literature from developing countries (e.g. Söderbom et al., 2006; Kuepie et al., 2009) we find convex returns to education. Returns to education hence increase with the level of education attained, hinting at the low quality of primary school education.[13] To illustrate the non-linearity of education, we tested a specification with education dummies instead of a continuous education variable. Returns to education are insignificant at very low levels of education (i.e. there are no significant returns to having completed primary education compared to having no schooling or incomplete primary education), but significant and increasing with the level of education obtained. Returns are highest for those who obtained a post-graduate degree (see Table A3 in the Appendix). This pattern suggests that the quality of primary education in Bangladesh might be quite low. One has to keep in mind that the data set used for this paper only covers the formal sector, which might exhibit different rewards to educational attainment (Kuepie et al., 2009).

Including measures of cognitive skills in the wage regressions shows that cognitive skills have a positive effect on wages, even when controlling for educational attainment. However, returns are rather low: a one standard deviation increase in the literacy score increases wages by 3 percent. Estimates for developed countries are larger (ranging between 3.8 percent in Sweden to 20 percent in the United States) (Hanushek and Zhang, 2009) though these estimates look at annual earnings and not wages. Estimates for developing countries are generally found to be above those for developed countries (Hanushek and Woessmann, 2008). The rather small effect of literacy could be due to the highly selected sample we are looking at which considers men working in formal firm in an economy which is largely informal.

Extraversion is found to have a positive effect on wages: a one standard deviation increase in this personality trait increases wages by almost 2 percent. This is equivalent to Heineck and Anger (2010) who also find a 2 percent wage premium for a one standard deviation increase in extraversion among males in their German sample. Further, we see a negative and not trivial effect of grit on wages (-1.7 percent). This effect is rather surprising since literature would have suggested that perseverance and a passion for long-term goals correlate positively with wages. Díaz et al. (2013) use data for Peru and find that conditional on schooling, grit has a positive effect on average earnings. The Peruvian data set includes a 17-item grit scale which allows the authors to distinguish between two measures of grit: consistency of interest and persistence of effort. Positive and significant

[13]To compare our results to other studies looking at the returns to formal education in Bangladesh, we also estimated a basic model linear in the education term. We find a return of about 6.9 percent to an additional year of education. This estimate is in line with estimates from Asadullah (2006) who uses a national household survey from 1999-2000 for Bangladesh and finds returns of 6.2 percent for men, and higher returns in urban than rural areas. However, as our squared years of education term is highly significant, we will continue with a non-linear specification of education.

results are only found for persistence of effort, the coefficient for consistency of interest is negative, while insignificant. The negative effect of grit could hence be due to our questionnaire rather focusing on the consistency of interest aspect of grit. Overall, the OLS model, while simplistic and probably biased, is able to explain about half of the wage variation observed in our sample.

5.3 Choice of hiring channel

The OLS estimates of returns to skills presented in the previous section are likely to be biased, if the skills variables we are looking at (cognitive and non-cognitive) are predicting the hiring channel an individual chooses. Table 4 presents a logit model in which the dependent variable is the probability of having been hiring through social networks. This model is the first equation of the selection model which will follow (5). Results are depicted in Table 4. A higher number of years of education reduces the probability of having found the current work through social networks. Cognitive skills (literacy) also has a negative effect on the probability of using networks. This makes sense intuitively, since individuals who are barely able to read are not able to access the necessary information to engage in formal job search (such as newspaper ads). Looking at the non-cognitive skills, no personality trait seems to affect the probability of having found the job through social networks. Table 4 further confirms our identifying variable: if the mother has no formal education, a worker is more likely to have found his job through networks.

The choices for a worker (and for a firm) to search (hire) through social network could be different depending on the occupation to be filled. We looked separately at white collar and blue collar workers to understand what determines their probability to have been hired through social networks (the last two columns of Table 4). For blue collar workers, years of education is the only significant predictor: having obtained more years of education significantly lowers the probability of having been hired through social networks. For white collar workers, it is not years of education but the literacy score which has a significant and negative effect. Moreover, white collar workers who are more emotionally stable and less gritty have an increased probability of having found a job through networks. Emotionally stable individuals are probably more likely to have continued relationships with a larger network, increasing their chances to receive job offers through this network. Gritty workers are more willing to continue searching for employment using formal channels, even though this might take longer.

For now, we grouped all types of social networks into one category. However, the type of social network activated might matter for wage returns. Also, the predictors might be different depending on the type of social network used for hiring. We hence estimate a multinomial logit model, distinguishing between one formal hiring channel and 4 different types of social networks (family, friends, village connections, and political and school alumni associations). The number of observations within each channel is quite balanced, except for the last category.[14] Table 5 shows depicts the result. A higher reading score is again related to a higher probability of having found the job through formal channels (column 1), but a lower probability of having found the job through family or friends (columns 2 and 3 respectively). The literacy score is not significant in the village or political and school association channels. Instead, scoring higher on the numeracy test is associated with a lower probability of having found the job through political and school associations, though the effect is very small, and with a higher probability of having found work through family members.

Once we distinguish between different types of social networks, non-cognitive skills also affect the choice of hiring channel. Agreeableness has a positive effect on having found the job through one's family, as does grit. This suggests that families might be more willing to recommend their relatives if they perceive them to be friendlier and more willing to work in the pursuit of long term goals. The probability of having been hired via a friend increases with a higher score on conscientiousness and hostile attribution bias; it decreases with a higher score on grit. Friends could be more willing to recommend their peers if they perceive them to be hard-working and well organized (conscientiousness), while workers might be more willing to ask friends for help with whom they are sure of good intentions (hostile attribution bias). Workers who are perseverant and willing to commit to longer term goals will probably wait for a (better) offer through the formal hiring channel and not accept friends' offers. Lastly, those who found their job via village networks tend to have a lower hostile attribution bias. They are hence less likely to assume that others' have hostile intentions and might be more willing to accept help of weaker connections.

5.4 Skills and endogenous hiring channel

The results from the previous section show that cognitive and non-cognitive skills influence the selection of the hiring channel. Switching models are able to take into account the endogeneity of the hiring channel in estimating wage returns to the different skills. Table 6 presents the results, modeling selection as a bimodial choice between formal channels and networks.[15]. Columns 1-3 of Table 6 depict the wage regression for the formal hiring channel (equation (2)) and columns 4-6 the wage regression for the network hiring channel (equation (3)), with a set of covariates that are successively added to the basic specification.

Literacy skills, which were highly significant in the OLS regressions and in the selection equation, are not statistically significant in either the formal hiring channel or the network hiring channel, once the initial selection into type of hiring channel has been controlled for. Numeracy is not significant either. Cognitive skills hence only act

[14] 960 workers found their job through family members, 1,012 through friends, 489 through village connections, but only 76 men found their job through political and school alumni associations.

[15] The selection equation (equation (4)) is depicted in Table 4.

upon enabling workers to access the formal hiring channel by being able to read job advertisements. Workers hired formally are then paid a wage premium for having been selected through this channel, hence the positive coefficient on literacy skills in the OLS regressions.

Non-cognitive skills on the other hand, enjoy a wage return independently of their impact on hiring channel selection. For those who were hired through formal channels, a one standard deviation increase in the personality trait extraversion leads to a 3.5 percent increase in wages. This is larger than the 1.8 percent increase per standard deviation that we found in the OLS regressions. Extraversion is only significant for those who found their job though formal channels, network hires are not rewarded for being more extroverted. Employers thus value their employees to be more outgoing, proactive and taking on leadership roles only if they were hired through formal channels. This hints at formal hires and network hires performing different tasks that require a different set of skills (e.g. leading teams, coming up with new solutions). Further, hostile attribution bias and grit both have a significant (negative) effect on wages for those who found their job through formal channels. A higher value on the hostile attribution bias trait means that the worker is more likely to interpret others' behavior as hostile. In a work-environment in which workers interact with each others, cooperation with and openness towards other people is quite necessary, explaining the negative effect. The negative coefficient of grit on wages is surprising, since grit, the tendency to pursue long-term goals and to be perseverant is thought to correlated positively with wages. This effect was also found in the OLS regressions and hence persists once selection into hiring channel is being accounted for. Among network hires the only personality trait that is rewarded is emotional stability, which has been linked to better task performance. Finally, years of education are convex, increasing and significant in both channels (formal and networks), though at the average number of years of education (12.8 in the formal channel, 7.2 in the network channel), returns are positive in the formal channel, but negative in the network channel.

Comparing the results from the endogenous switching model to separate OLS regressions by hiring channel shows that returns to the non-cognitive skills are quite similar (Table A5). The coefficients have the same sign and are of similar size. Hostile attribution bias, which is significant in the switching model, has the same sign but is insignificant in the OLS models. As expected, literacy has a positive significant effect in the OLS which disappears once selection into hiring channel is taken into account.

The different rewards to skills by hiring channel give rise to the notion that firms might hire workers through the different channels depending on their occupation (i.e. blue collar workers being hired predominantly through social networks, while white collar workers are hired largely through formal channels). The data does not fully discourage this claim: about 40 percent of workers in the sample work in blue collar jobs and 78 of them have been hired through networks (compared to only 39 percent of workers of white collar occupations). Looking at correlations between occupations and hiring channels finds evidence for professionals and clerical support workers to be hired predominantly through formal channels, though the correlations are not strong (Table A4). To make sure that the effect that we are capturing is not purely by occupation (blue collar/ white collar), and to allow for differential returns to cognitive and non-cognitive skills by occupation, we introduce interactions with being a white collar worker (Table 7).

Adding interactions between the cognitive as well as personality trait variables and a dummy for being a white collar worker does not change the results for those who were hired through networks: all interaction terms are insignificant and emotional stability remains the only significant personality trait, irrespective of whether the worker is in a blue collar or a white collar occupation. In the formal hiring channel differential returns to personality skills by occupation type (white or blue collar) are visible, though cognitive skills remain insignificant. Conscientiousness and hostile attribution bias are rewarded positively among blue collar workers, but negatively among white collar workers. Conscientiousness captures the ability to be hard working but also rule following and to exhibit planned instead of spontaneous behavior. Grit shows a negative effect on wages, however, the effect for white collar workers is smaller (though the interaction is not significant). Additionally, the interaction between openness to experience and being a white collar worker is positive and significant.

All in all, it seems that among those hired formally, the personality traits rewarded match rather closely the task description of the occupation. Most notably, blue collar workers are rewarded for personality traits that enable them to work on clearly defined and possibly repetitive tasks (conscientiousness, hostile attribution bias, and lower grit), while white collar workers are rewarded for traits that enable them be more creative and open towards new situations (openness to experience). However, these different rewards only show among those hired formally; among those hired through networks the only trait that is rewarded across the board is emotional stability.

To further understand whether the non-differentiated effect of personality for those hired through networks comes from grouping all types of social networks into one category, we estimate the endogenous switching model with a multinomial selection model with five different states, one formal hiring channel and four informal hiring channels (family, friends, village connections, and school alumni and political associations). Table 8 depicts wage returns to skills, taking into account this multinomial selection. The positive effect of emotional stability for those who found their jobs through networks remains but is no longer statistically significant in the different network types. Further, while agreeableness positively influences the probability of having found a job through family networks, once this selection is controlled for, being more agreeable does not seem to pay off in the family channel or in the village channel, but does have a positive effect for those who found their job through friends, or political associations (again, not statistically significant). For those who found their job through friends, a higher score on the numeracy tests exhibits negative wage returns (significant at the 10 percent level).

We further looked at the selectivity correction terms (ρ) to obtain information about the pattern of selection based on unobserved characteristics that we aim to correct. First, we look at the bimodial model (Table 6). In this model, we see that $\rho 1$, the selection coefficient related to the formal hiring channel selection equation is negative in the formal hiring wage equation. This means that people who would have benefited from other hiring channels have been hired through the formal channel. Besides, the coefficient related to the formal sector selection equations is also negative and significant in the network wage equation, thus people who have been hired through networks would have performed better on the basis of their observed skills, had they been hired through formal channels.

Taking into account multinomial instead of bimodial selection in the first stage reveals a positive selectivity of individuals out of the village into the formal hiring channel, out of the politics and school alumni hiring channel into the friends, and out of the friends into the village hiring channel. This is suggesting that some individuals who would not have found jobs through some channels (villages in the first case) manage to find jobs through other channels (the formal hiring channel in the first case) and perform well on their job given their hiring channel. Interestingly, once we look at subcategories of network hiring, none of the selection coefficients related to the formal hiring channel selection equation are significant; also, they are only negative in the friends and the politics and school hiring channel. This suggests that the type of network hiring channel matters in the sense that given individual heterogeneity, some individuals do actually benefit from having found their job through specific hiring channel.

5.5 Starting and current wages

In addition to looking at current wages, an analysis of starting wages is informative especially when it comes to the evaluation of returns to skills. Employers might not be able to fully observe a worker's set of skills at the time of hiring; instead, skills and productivity are only fully revealed over time ('employer learning'). Employers are assumed to use school attainment and other observable signals (such as information revealed during hiring interviews, or information obtained through others sources such as networks) to predict productivity and set starting wages accordingly. Over time, wages are then adjusted to actual observed productivity. The different hiring channels hence also offer opportunities for employers to obtain information about a potential employee prior to hiring - either through information obtained via the formal hiring process (such as personal interviews or assessment centers), or by means of information received via social networks (e.g. thanks to which connection the applicant has heard of the job, or who recommended the applicant, or personal information about the applicant through the recommending person).[16]

[16]Non-cognitive skills are assumed to be rather stable in adult life (Cobb-Clark and Tan, 2011). The majority of our sample was hired in their mid-twenties (mean age at time of hiring is 26 years). We are hence assuming that while the assessment of skills was conducted after the worker had started their current job, this does not affect their measurement.

Table 9 presents the switching model for starting wages, current wages, and wage growth. Looking at the starting wage regressions reveals the importance of education and prior experience in determining wages, which constitutes the part of a worker's skills set that can rather easily be observed at the time of hiring. In the formal hiring channel, an increase in the numeracy score is associated with a lower starting wage, even after controlling for selection into hiring channel. This effect is not visible for current wages, and is rather curious. Further investigation reveals that this effect is driven by older workers (55 years and older) and those who have been employed in their current job for a longer period of time. Two explanation seem likely: either a selection effect is at work, which means that older workers who have a higher numeracy were able to stay on the job for longer, or a learning effect is in place, suggesting that over time, workers acquire the necessary math skills on the job.

Extraversion has a positive and significant effect on both starting wages and current wages in the formal hiring channel. Extraversion is arguably a character trait that is rather easily observable during job interviews. Employers looking for that specific character trait are hence able to screen applicants and award them accordingly. Emotional stability also has a positive effect on starting wages, for both hiring channels; however, this effect disappears over time for formal hires. The coefficient on openness to experience among network hires is negative and significant in the starting wage regressions and negative but insignificant in the current wage regressions. Openness to experience is related to intellectual curiosity but also to autonomy and non-conformity, not necessarily a desirable trait. For those hired formally, openness to experience is always positive, but never statistically significant.

Grit and hostile attribution bias are not significant in the starting wage regressions, but negative and significant in the current wage regressions. Concerning grit, we have already shown that the negative effect of grit develops with tenure, and in fact stems fully from workers who have stayed at their current job for more than 5 years (see Table A6). These seem to be workers who possess a high persistence of effort, but who might not be terribly productive at their job and therefore missed out on raises or promotions. The negative effect of hostile attribution bias on the other hand is driven by those with shorter tenure (up to 5 years at the current firm), for whom it is probably necessary to find their way into the functioning and hierarchy of the new establishment. Perceiving co-workers as hostile might hamper productivity. Both grit and hostile attribution bias are hard to observe at the hiring stage and therefore do not influence wage setting when the worker is hired. Taking wage growth instead of current wages or starting wages as the dependent variable reveals a small significantly positive effect of conscientiousness for those have been hired through networks. Two conflicting explanations seem likely: While it is possible that conscientiousness positively predicts wage growth, it is also imaginable that a worker becomes more conscientiousness over time to comply with the requirements of his job. Unfortunately, the data does not allow us to distinguish between them.

5.6 Determinants of the within-firm wage gap between formal and network hires

Finally, we try to understand whether employer biases and preferences can help explain part of the wage gap between formal and network hires, exploring the employer side of this matched survey. Results for this section are based on a restricted sample of firms that have at least two formal and two informal hires, leaving us with 171 firms, 1,251 formal hires and 1,279 network hires (about a third of the sample used in previous sections). Table A7 presents characteristics of the firms included in this restricted sample in comparison to the sample of firms used in previous sections. The reduced sample contains a slightly higher share of firms from the education sector and a slightly smaller share of firms from the public administration sector. Firms in the reduced sample are on average bigger than firms in the original sample, which is to be expected since we impose the restriction of having at least two formal and two network hires per firm. Table A8 presents a similar comparison for workers. Few differences between workers can be observed apart from a slightly better educational attainment among workers in the reduced sample.

The previous sections have shown that different types of skills have varying returns to wages, which is affected further by the hiring channel through which workers found their jobs. The differential returns to the same skill type varying by hiring sector leads to wage gaps between similar workers within the same firms. This could in fact reflect preferences of firms for certain skill sets among certain types of hires. To the degree to which employers value some skills more and have underlying assumptions or information about the availability of these skills in different hiring channels (formal/networks) this could affect the wage premium paid. We employ a hierarchical modeling approach (Bryk and Raudenbush, 1992; Meng, 2004; Nordman and Wolff, 2009; Nordman et al., 2015) to capture the determinants of this within-firm formal-network hiring channel wage gap. Decomposing this wage gap allows us to better understand which employer biases or preferences predict a larger or smaller gap.

We start by including firm fixed effects in our worker-level wage equations for formal and network hires:

$$lnw_{ij}^F = \beta_0^F + \beta_1^F A_i + \beta_2^F Cog_i + \beta_3^F NonCog_i + \epsilon_{ij}^F + \phi_j^F \tag{6}$$

$$lnw_{ij}^N = \beta_0^N + \beta_1^N A_i + \beta_2^N Cog_i + \beta_3^N NonCog_i + \epsilon_{ij}^N + \phi_j^N \tag{7}$$

In the regression analysis, we control for a worker's demographic characteristics, A, their cognitive skills (Cog) and non-cognitive skills ($NonCog$). Due to these controls, the effect of the firm fixed effect, ϕ, then simply reflects a premium paid by the firm to its employees beyond their observable characteristics. The difference between ϕ_j^F and ϕ_j^N can hence be interpreted as an estimate of the within-firm wage premium or penalty for having been hired through formal channels. We then use OLS regressions with the difference in firm fixed effects as the dependent variable to estimate the effect of firm level characteristics on the size of the within-firm wage gap.

$$\widehat{\phi}_j^F - \widehat{\phi}_j^N = \beta_0 + \beta_1 C_j + \beta_2 SkillsEmployees_j + \beta_3 SkillsHiring_j + \epsilon_j \tag{8}$$

where C_j is a vector of firm characteristics at the firm level including industry, firm size, whether the firm exports, whether it provides on the job training, and the gender and education of the top manager. Respondents of the employer survey (a high ranking manager of the firm) were further asked to judge the importance of a battery of skills and values among their employees and the importance of a number of skills in the hiring decision. Standardized values of these skills variables are also included (vectors $SkillsEmployees_j$ and $SkillsHiring_j$, respectively). We normalize the within-firm wage gap so that it is bound in the (0,1] interval: $wg_j = e^{-(\widehat{gap}_{max} - \widehat{gap}_j)}$ where $\widehat{gap}_{max}$ is the sample maximum of the estimated within-firm wage gap and $\widehat{gap}_j$ is the estimated wage gap for formal and network hires within-firm j. The sample mean is low at 0.14, as the distribution is quite skewed. We drop the 5 most unequal firms, which leaves us with a sample mean of 0.39.[17] Figure A4 depicts the distribution of the normalized within-firm wage gap by industry. The within-firm wage gap between formal and network hires does not seem to be concentrated in one industry.

Results are displayed in Table 10. Larger firms are associated with a lower within-firm wage gap between workers hired through networks and through formal channels. In addition, firms that export also exhibit a higher wage gap compared to firms in the commerce sector, as do firms that have a formal performance review.

We continue by including standardized scores capturing the importance the employer places on different types of skills among its employees and standardized scores dealing with the importance employers place on different hiring criteria. Employers were asked (on a scale of 1-10) how important they think it is for their employees to have the following skills: communication, team work, problem solving, literacy, numeracy, costumer care, responsibility, motivation, creativity, as well as general and advanced vocational job-specific skills. They were also asked (on a scale of 1-10) how important the following criteria are for their hiring decision: academic performance, work experience, skill set, interview, informal network/recommendation, and political affiliation.

Results show that the importance that employers attribute to a range of skills are significant determinants of the within-firm wage gap. A one standard deviation increase in the perceived importance of communication skills reduces the wage gap, while a similar increase in the perceived importance of literacy skills increases the gap. Similarly, the importance of hiring criteria has statistically significant effects on the within-firm wage gap. A one standard deviation increase in the perceived importance of academic performance increases the gap, while a similar increase in the perceived importance of interview performance decreases it. Workers who are hired through social

[17] The firms that we drop come from almost all industries (1 manufacturing, 1 public administration, 1 education and 2 finance).

networks are hence paid more equally if employers think interviews are important in the hiring decision and are therefore more likely to interview all candidates, suggesting statistical discrimination, rather than taste discrimination.[18] None of the industry dummies included are statistically significant. The R^2 shows that we can only explain about 18 percent of the variation of the within-firm wage gap.

6 Conclusion

This paper provided estimates for the wage returns to different types of skills (educational attainment, cognitive skills and non-cognitive skills) using a novel matched employer-employee data set from Bangladesh. We aimed to take into account both the direct and indirect effects of non-cognitive skills on wages, focusing on one indirect feature - the choice of hiring channels. The interplay between different skills and hiring channels in determining labor market outcomes is an important issue especially in developing countries in which the role of informal networks is large and research on the effects of non-cognitive skills scarce.

We find that reading skills have a positive effect on mean wages, even when controlling for educational attainment. Numeracy, however, is not found to have an effect. Effects of personality on wages differ by hiring channel. We incorporate the fact that the same unobserved characteristics could drive both, the selection of the hiring channel and the wage through an endogenous switching model.

We model the selection process as a bimodial and multinomial logit model as workers face not only a choice between a formal channel and social networks, but also between types of social networks (friends, family, or connections within the village) as the type of network used is likely to have an effect on wages. We find that a higher score on the literacy test increases the probability to choose formal hiring channels and decreases the probability to have found the job through friends or family. Literacy does not have an effect on having found the job through village connections. Non-cognitive skills also have an impact on the decision of which hiring channel to choose: more agreeable individuals are more likely to have found their job through family members, while individuals who are emotionally stable have a higher probability of having found the job through village connections.

We find that the cognitive skills (literacy) affect wages only through increasing the probability to chose the formal over other hiring channels. Once this initial selection into hiring channel has been corrected for, there is no further significant wage return to literacy. Non-cognitive skills (extraversion) exhibit positive and significant returns to wages for those hired through formal channels. In this channel, one standard deviation increase in the personality trait is associated with a 3 percent increase in wages, which is quite high

[18]Statistical discrimination refers to the use of group averages to obtain information in the absence of direct information about productivity. Employers may not know worker's productivity for sure and hence base their assessment on observable characteristics such as the hiring channel. Workers who are performing better than the group average then suffer unfair discrimination.

if compared to average returns to education in developing countries (Psacharopoulos and Patrinos, 2004).

Additionally, we explore demand-side preferences for specific skills by decomposing the within-firm formal-network wage gap to better understand whether it is driven by firm characteristics or preferences for specific skills. We find that employers who value interviews and literacy are associated with a smaller wage gap between workers who found their job through the formal channel or through social networks, but employers who value communication skills and formal education are associated with a larger wage gap.

This paper illustrates that literacy remains an important aspect in developing countries in order to enable workers to access their full potential - here, being hired through formal channels - even though it might not have an additional wage return apart from facilitating this first selection. Further, returns to non-cognitive skills are comparable to developed countries. This was not a priori a given and could stem from the fact that the sample used for this analysis (male workers in the formal sector in Bangladesh) is likely to be very selected. More research on the returns to non-cognitive skills in different parts of the labor market in developing countries such as rural areas or the informal labor market would help shed further light on the role of non-cognitive skills in developing countries' labor markets.

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Figure 1: Conceptual framework illustrated

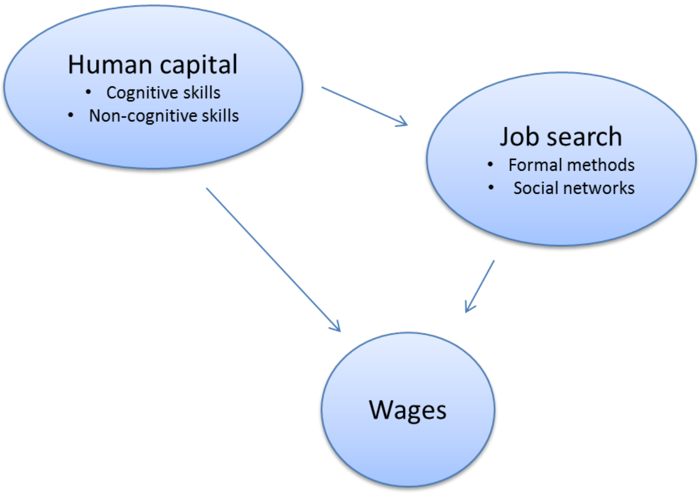

Table 1: Characteristics of firms in sample

Share of firms	Original	Restricted
Commerce	0.150	0.150
	(0.36)	(0.36)
Education	0.150	0.154
	(0.36)	(0.36)
Finance	0.150	0.148
	(0.36)	(0.36)
Manufacturing	0.400	0.396
	(0.49)	(0.49)
Public administration	0.150	0.152
	(0.36)	(0.36)
At most 20 employees	0.382	0.376
	(0.49)	(0.48)
21 - 70 employees	0.232	0.236
	(0.42)	(0.43)
More than 70 employees	0.386	0.388
	(0.49)	(0.49)
Firm located in Dhaka	0.528	0.528
	(0.50)	(0.50)
Main channel of job advert: networks	0.336	0.331
	(0.47)	(0.47)
One channel of job advert: networks	0.540	0.536
	(0.50)	(0.50)
Observations	500	487

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS). The restricted sample consists of male workers with non-missing skills variables only. Standard deviation in brackets.

Table 2: Characteristics of employees

Employees	All	Formal Hires	Network Hires
Log Hourly Current Wage	3.62	3.89	3.39
	(0.61)	(0.59)	(0.51)
Married	0.77	0.83	0.72
	(0.42)	(0.37)	(0.45)
Age	31.68	33.30	30.31
	(8.38)	(8.10)	(8.37)
Age at hiring	26.04	26.88	25.33
	(6.47)	(5.86)	(6.86)
Previous experience (years)	1.98	1.94	2.02
	(3.11)	(3.15)	(3.07)
Tenure (years)	5.63	6.42	4.97
	(5.66)	(6.24)	(5.02)
Manager	0.05	0.05	0.06
	(0.22)	(0.22)	(0.23)
Skilled white collar	0.55	0.76	0.38
	(0.50)	(0.43)	(0.48)
Skilled blue collar	0.27	0.10	0.41
	(0.44)	(0.30)	(0.49)
Unskilled	0.13	0.09	0.16
	(0.34)	(0.29)	(0.37)
Lives in capital (Dhaka)	0.59	0.51	0.65
	(0.49)	(0.50)	(0.48)
Primary schooling	0.31	0.07	0.50
	(0.46)	(0.26)	(0.50)
Secondary schooling	0.46	0.49	0.43
	(0.50)	(0.50)	(0.50)
Tertiary schooling	0.23	0.44	0.06
	(0.42)	(0.50)	(0.24)
Reading score	4.62	5.99	3.45
	(2.60)	(2.02)	(2.47)
Numeracy score	5.71	6.36	5.16
	(2.01)	(1.66)	(2.11)
Extraversion	6.43	6.41	6.45
	(1.58)	(1.56)	(1.59)
Openness to experience	7.52	7.68	7.39
	(1.89)	(1.95)	(1.83)
Conscientiousness	7.53	7.65	7.44
	(1.86)	(1.91)	(1.81)
Emotional stability	7.75	7.65	7.84
	(1.86)	(1.90)	(1.82)
Agreeableness	7.34	7.45	7.26
	(1.96)	(1.98)	(1.94)
Hostile attribution bias	4.29	4.38	4.22
	(1.66)	(1.65)	(1.66)
Grit	7.45	7.60	7.32
	(1.87)	(1.90)	(1.83)
Found job through network	0.54	0.00	1.00
	(0.50)	(0.00)	(0.00)
Observations	4,678	2,141	2,537

Notes: Sample excludes employees for whom personality questions are missing (about 16 percent). Male workers only. Maximum score for literacy and numeracy is 8. Maximum score for the personality trait variables is 12. Standard deviation in brackets.

Table 3: Returns to skills

Log hourly wages	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	-0.008	-0.015*	-0.015*	-0.018**	-0.012	-0.018**
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Years of education (sqrd)	0.004***	0.004***	0.004***	0.004***	0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Prior experience	0.024***	0.024***	0.025***	0.022***	0.021***	0.018***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Prior experience (sqrd)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current firm	0.031***	0.031***	0.031***	0.032***	0.028***	0.029***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Tenure in current firm (sqrd)	-0.001***	-0.001***	-0.001***	-0.001***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.104***	0.105***	0.109***	0.118***	0.107***	0.113***
	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)
Reading score		0.030*	0.028*	0.028*	0.031**	0.027*
		(0.016)	(0.015)	(0.016)	(0.015)	(0.016)
Numeracy score		-0.001	0.001	0.002	0.000	-0.000
		(0.016)	(0.016)	(0.015)	(0.016)	(0.015)
Extraversion			0.018	0.018*	0.017	0.018*
			(0.011)	(0.011)	(0.011)	(0.010)
Openness to Experience			0.007	0.007	0.004	0.002
			(0.011)	(0.011)	(0.011)	(0.010)
Conscientiousness			0.008	0.002	0.011	0.006
			(0.010)	(0.010)	(0.010)	(0.010)
Emotional Stability			0.014	0.013	0.015	0.014
			(0.011)	(0.011)	(0.010)	(0.010)
Agreeableness			0.005	0.004	0.004	0.006
			(0.011)	(0.010)	(0.010)	(0.010)
Hostile Attribution bias			0.001	0.001	0.002	0.000
			(0.010)	(0.010)	(0.010)	(0.010)
Grit			-0.009	-0.013	-0.012	-0.017*
			(0.010)	(0.010)	(0.010)	(0.010)
Firm characteristics				YES		YES
Occupation dummies					YES	YES
Constant	2.948***	3.000***	2.995***	2.875***	3.170***	3.090***
	(0.045)	(0.049)	(0.048)	(0.123)	(0.059)	(0.121)
Observations	4,678	4,678	4,678	4,678	4,678	4,678
R^2	0.466	0.467	0.468	0.485	0.490	0.513

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Probability of getting a job using social networks: marginal effects

Probability of getting a job through networks	All	Blue collar workers	White collar workers
Years of education	-0.043***	-0.024**	-0.021
	(0.014)	(0.012)	(0.021)
Years of education (sqrd)	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
Prior experience	0.007	0.023**	0.001
	(0.007)	(0.010)	(0.008)
Prior experience (sqrd)	-0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)
Tenure in current firm	-0.000	-0.004	0.002
	(0.005)	(0.006)	(0.006)
Tenure in current firm (sqrd)	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Reading score	-0.083***	-0.009	-0.121***
	(0.022)	(0.018)	(0.023)
Numeracy score	0.021	0.013	0.019
	(0.019)	(0.013)	(0.021)
Married	-0.070**	-0.019	-0.082**
	(0.031)	(0.024)	(0.036)
Extraversion	0.004	-0.006	0.014
	(0.014)	(0.011)	(0.014)
Openness to Experience	-0.002	-0.011	0.010
	(0.014)	(0.012)	(0.015)
Conscientiousness	0.019	0.019	0.006
	(0.015)	(0.013)	(0.016)
Emotional Stability	0.013	-0.008	0.028*
	(0.013)	(0.011)	(0.015)
Agreeableness	0.012	0.015	0.001
	(0.013)	(0.011)	(0.016)
Hostile Attribution bias	-0.013	-0.005	-0.016
	(0.013)	(0.010)	(0.015)
Grit	-0.020	0.000	-0.029*
	(0.013)	(0.012)	(0.015)
Mother no formal education	0.133***	0.064***	0.127***
	(0.027)	(0.023)	(0.031)
Household size	0.005	-0.001	0.008
	(0.009)	(0.008)	(0.009)
Observations	4,678	1,852	2,826
Pseudo R^2	0.370	0.284	0.312

Notes: Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1; Marginal effects reported are at the means of covariates. Control variables include occupation dummies and firm characteristics.

Table 5: Probability of getting a job through different hiring channels: marginal effects

Probability of getting a job through different hiring channels	(1) Formal	(2) Family	(3) Friends	(4) Village	(5) Politics & School
Years of education	0.042***	-0.016*	-0.012	-0.014***	-0.001
	(0.014)	(0.008)	(0.008)	(0.004)	(0.002)
Years of education (sqrd)	0.001	-0.000	-0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Prior experience	-0.008	-0.002	0.007	0.004	-0.001
	(0.008)	(0.006)	(0.005)	(0.004)	(0.002)
Prior experience (sqrd)	0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current firm	-0.000	0.003	-0.005	0.001	0.001
	(0.006)	(0.004)	(0.004)	(0.002)	(0.001)
Tenure in current firm (sqrd)	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.070**	-0.036*	-0.006	-0.022*	-0.005
	(0.031)	(0.022)	(0.019)	(0.012)	(0.005)
Reading score	0.086***	-0.061***	-0.029**	0.003	0.002
	(0.022)	(0.015)	(0.014)	(0.008)	(0.003)
Numeracy score	-0.024	0.023*	0.003	0.007	-0.008***
	(0.020)	(0.013)	(0.012)	(0.007)	(0.002)
Extraversion	-0.003	0.001	-0.006	0.007	0.002
	(0.014)	(0.010)	(0.010)	(0.008)	(0.002)
Openness to Experience	0.002	-0.014	0.006	0.005	0.001
	(0.014)	(0.012)	(0.010)	(0.006)	(0.002)
Conscientiousness	-0.020	0.005	0.025**	-0.009	-0.001
	(0.016)	(0.010)	(0.011)	(0.006)	(0.002)
Emotional Stability	-0.012	0.005	-0.002	0.007	0.003
	(0.013)	(0.009)	(0.009)	(0.006)	(0.002)
Agreeableness	-0.013	0.019*	-0.002	-0.004	0.000
	(0.013)	(0.010)	(0.009)	(0.005)	(0.002)
Hostile Attribution bias	0.012	-0.002	0.017*	-0.021***	-0.005***
	(0.014)	(0.009)	(0.009)	(0.006)	(0.002)
Grit	0.021	0.030***	-0.043***	-0.008	-0.000
	(0.013)	(0.010)	(0.010)	(0.006)	(0.002)
Mother no formal education	-0.134***	0.034*	0.054***	0.044***	0.003
	(0.027)	(0.018)	(0.018)	(0.013)	(0.004)
Household size	-0.006	0.001	0.009*	-0.001	-0.003*
	(0.009)	(0.006)	(0.006)	(0.003)	(0.002)
Observations	4,678	4,678	4,678	4,678	4,678
Pseudo R^2	0.219	0.219	0.219	0.219	0.219

Notes: Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1; Marginal effects reported are at the means of covariates. Control variables include occupation dummies and firm characteristics.

Table 6: Returns to skills using an endogenous switching model

Log hourly wages	(1) Formal	(2) Formal	(3) Formal	(4) Networks	(5) Networks	(6) Networks
Years of education	-0.077*	-0.065**	-0.033	-0.043***	-0.037***	-0.024**
	(0.041)	(0.033)	(0.025)	(0.014)	(0.012)	(0.010)
Years of education (sqrd)	0.005***	0.004***	0.003***	0.005***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Prior experience	0.039***	0.030***	0.027***	0.022**	0.018**	0.015*
	(0.011)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Prior experience (sqrd)	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current firm	0.024***	0.023***	0.025***	0.036***	0.032***	0.031***
	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Tenure in current firm (sqrd)	-0.000	-0.000	-0.000	-0.001***	-0.001***	-0.001**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Married	0.037	0.048	0.071**	0.073***	0.082***	0.101***
	(0.038)	(0.039)	(0.033)	(0.026)	(0.028)	(0.026)
Reading score	-0.032	-0.015	0.010	-0.034	-0.026	-0.014
	(0.038)	(0.033)	(0.030)	(0.025)	(0.022)	(0.023)
Numeracy score	-0.013	-0.011	-0.023	0.016	0.011	0.015
	(0.026)	(0.025)	(0.026)	(0.019)	(0.017)	(0.017)
Extraversion	0.033*	0.034**	0.035***	0.014	0.011	0.008
	(0.017)	(0.016)	(0.013)	(0.014)	(0.014)	(0.012)
Openness to Experience	0.025	0.022	0.022	-0.015	-0.020	-0.016
	(0.016)	(0.015)	(0.015)	(0.017)	(0.014)	(0.012)
Conscientiousness	0.015	0.018	0.007	0.020	0.022	0.013
	(0.017)	(0.016)	(0.017)	(0.015)	(0.014)	(0.013)
Emotional Stability	0.004	0.005	0.003	0.034**	0.034**	0.030**
	(0.015)	(0.016)	(0.014)	(0.015)	(0.013)	(0.012)
Agreeableness	0.012	0.006	0.005	0.012	0.012	0.010
	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)
Hostile Attribution bias	-0.030*	-0.031**	-0.025*	0.002	0.007	0.009
	(0.017)	(0.015)	(0.014)	(0.014)	(0.015)	(0.015)
Grit	-0.032*	-0.034**	-0.034**	-0.006	-0.013	-0.016
	(0.018)	(0.017)	(0.016)	(0.013)	(0.013)	(0.012)
Occupation dummies		YES	YES		YES	YES
Firm characteristics			YES			YES
$\rho 1$	-0.922***	-0.952***	-0.689***	-0.862*	-0.863**	-0.102
	(0.279)	(0.211)	(0.214)	(0.502)	(0.387)	(0.444)
$\rho 2$	0.357	0.122	0.254	0.182	0.095	0.430
	(0.383)	(0.346)	(0.318)	(0.372)	(0.260)	(0.290)
Constant	4.074***	4.194***	3.712***	2.962***	3.182***	3.186***
	(0.352)	(0.319)	(0.265)	(0.055)	(0.081)	(0.123)
Observations	2,141	2,141	2,141	2,537	2,537	2,537

Notes: Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Returns to skills - Differentiated returns

Log hourly wage	Formal	Networks
Years of education	-0.032	-0.030***
	(0.023)	(0.011)
Years of education (sqrd)	0.004***	0.005***
	(0.001)	(0.001)
Reading score	-0.005	-0.024
	(0.038)	(0.025)
Numeracy score	-0.004	0.031
	(0.033)	(0.021)
Extraversion	0.025	0.010
	(0.028)	(0.016)
Openness to Experience	-0.033	-0.023
	(0.028)	(0.016)
Conscientiousness	0.073**	0.002
	(0.028)	(0.019)
Emotional Stability	-0.011	0.035**
	(0.026)	(0.016)
Agreeableness	-0.021	0.013
	(0.027)	(0.017)
Hostile Attribution bias	0.041*	0.003
	(0.025)	(0.015)
Grit	-0.057**	0.005
	(0.029)	(0.015)
Reading#White	0.005	0.048
	(0.039)	(0.032)
Numeracy#White	-0.025	-0.043
	(0.041)	(0.029)
EX#White	0.013	-0.006
	(0.029)	(0.022)
OP#White	0.078**	0.022
	(0.033)	(0.023)
CO#White	-0.089***	0.016
	(0.029)	(0.023)
ES#White	0.019	-0.023
	(0.029)	(0.023)
AG#White	0.032	-0.016
	(0.032)	(0.024)
HB#White	-0.077***	0.016
	(0.029)	(0.022)
GR#White	0.025	-0.028
	(0.036)	(0.021)
$\rho 1$	-0.642***	-0.094
	(0.211)	(0.510)
$\rho 2$	0.671**	0.146
	(0.298)	(0.308)
Constant	3.548***	2.954***
	(0.271)	(0.126)
Observations	2,141	2,537

Notes: Controls include indvl and firm characteristics. White collar occupations are managers, professionals, clerks, service and sales workers. Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Returns to skills using an endogenous switching model - Multiple hiring channels

Log hourly wages	Formal	Family	Friends	Village	Politics & School
Years of education	-0.025	-0.015	0.000	-0.008	-0.285
	(0.024)	(0.022)	(0.022)	(0.035)	(0.272)
Years of education (sqrd)	0.003***	0.003**	0.003**	0.003*	0.019
	(0.001)	(0.001)	(0.001)	(0.002)	(0.014)
Prior experience	0.029**	0.034	-0.021	0.017	0.014
	(0.015)	(0.021)	(0.018)	(0.034)	(0.471)
Prior experience (sqrd)	-0.000	-0.001	0.002	-0.000	-0.002
	(0.001)	(0.001)	(0.002)	(0.005)	(0.120)
Tenure in current firm	0.024***	0.022**	0.029**	0.033*	0.015
	(0.006)	(0.011)	(0.011)	(0.018)	(0.144)
Tenure in current firm (sqrd)	-0.000	-0.000	-0.001	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.009)
Married	0.073**	0.140**	0.113**	0.093	0.299
	(0.036)	(0.063)	(0.053)	(0.082)	(0.473)
Reading score	0.032	0.077	-0.005	-0.042	0.024
	(0.035)	(0.054)	(0.042)	(0.101)	(0.410)
Numeracy score	-0.030	-0.046	-0.067*	0.048	0.163
	(0.030)	(0.039)	(0.038)	(0.067)	(0.404)
Extraversion	0.038**	0.012	0.008	-0.031	0.091
	(0.016)	(0.029)	(0.024)	(0.041)	(0.208)
Openness to Experience	0.029*	-0.003	0.006	-0.003	0.098
	(0.016)	(0.030)	(0.025)	(0.046)	(0.192)
Conscientiousness	0.004	0.023	0.022	0.033	-0.235
	(0.020)	(0.027)	(0.032)	(0.060)	(0.274)
Emotional Stability	0.005	0.031	0.017	0.042	0.026
	(0.016)	(0.026)	(0.025)	(0.037)	(0.206)
Agreeableness	-0.002	-0.027	0.018	-0.013	0.045
	(0.015)	(0.031)	(0.026)	(0.045)	(0.222)
Hostile Attribution bias	-0.031*	-0.004	0.029	0.011	0.015
	(0.016)	(0.033)	(0.034)	(0.066)	(0.332)
Grit	-0.052**	-0.082	-0.052	-0.039	-0.091
	(0.024)	(0.062)	(0.050)	(0.075)	(0.341)
$\rho 1$	-0.283	0.301	-0.555	0.972	-0.754
	(0.255)	(0.590)	(0.385)	(0.758)	(0.733)
$\rho 2$	-0.493	-0.325	-0.862	0.196	-1.059
	(0.667)	(0.363)	(0.872)	(0.840)	(1.083)
$\rho 3$	0.836	1.180	0.278	1.420*	-1.700
	(0.706)	(0.902)	(0.290)	(0.855)	(1.135)
$\rho 4$	1.283*	0.800	-0.803	0.089	-0.226
	(0.714)	(0.730)	(0.832)	(0.376)	(1.052)
$\rho 5$	0.542	1.627	2.490**	1.309	0.048
	(1.220)	(1.139)	(1.115)	(1.369)	(0.329)
Constant	3.672***	4.228***	2.259***	3.908***	0.361
	(0.303)	(0.759)	(0.688)	(0.838)	(6.324)
Observations	2,141	960	1,012	489	76

Notes: Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1. Selection correction using Bourguignon et al. (2007). Control variables include occupation dummies and firm characteristics.

Table 9: Returns to skills using an endogenous switching model - Starting and current wage

	Starting wage		Current wage		Wage growth	
Log hourly wages	Formal	Network	Formal	Network	Formal	Network
Years of education	-0.022	-0.035**	-0.033	-0.024**	0.000	0.001
	(0.030)	(0.014)	(0.023)	(0.011)	(0.005)	(0.002)
Years of education (sqrd)	0.003**	0.004***	0.003***	0.003***	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Prior experience	0.032*	0.032***	0.027***	0.015*	0.005	0.003
	(0.020)	(0.011)	(0.009)	(0.009)	(0.006)	(0.002)
Prior experience (sqrd)	-0.001	-0.000	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Reading score	-0.059	-0.031	0.010	-0.014	-0.003	0.005
	(0.040)	(0.029)	(0.030)	(0.022)	(0.007)	(0.004)
Numeracy score	-0.066**	0.009	-0.023	0.015	0.003	-0.002
	(0.033)	(0.020)	(0.024)	(0.017)	(0.004)	(0.003)
Extraversion	0.037*	0.019	0.035**	0.008	-0.003	-0.004
	(0.021)	(0.019)	(0.014)	(0.014)	-0.004	(0.003)
Openness to Experience	0.013	-0.035**	0.022	-0.016	0.004	0.003
	(0.018)	(0.018)	(0.014)	(0.013)	(0.003)	(0.002)
Conscientiousness	-0.012	0.001	0.007	0.013	-0.001	0.006**
	(0.020)	(0.017)	(0.017)	(0.013)	(0.004)	(0.002)
Emotional Stability	0.046**	0.046***	0.003	0.030**	-0.003	-0.002
	(0.020)	(0.017)	(0.015)	(0.012)	(0.004)	(0.002)
Agreeableness	0.023	-0.003	0.005	0.010	0.001	-0.001
	(0.021)	(0.018)	(0.013)	(0.014)	(0.004)	(0.003)
Hostile Attribution bias	-0.015	-0.004	-0.025*	0.009	-0.000	0.002
	(0.020)	(0.016)	(0.014)	(0.013)	(0.003)	(0.002)
Grit	-0.013	0.003	-0.034**	-0.016	-0.001	-0.002
	(0.022)	(0.014)	(0.016)	(0.012)	(0.004)	(0.002)
$\rho 1$	-0.330	-0.583	-0.689***	-0.102	-0.248	-0.003
	(0.214)	(0.365)	(0.214)	(0.461)	(0.176)	(0.331)
$\rho 2$	0.567	0.153	0.254	0.430	-0.193	-0.162
	(0.345)	(0.297)	(0.339)	(0.297)	(0.285)	(0.227)
Constant	3.501***	2.802***	3.712***	3.186***	0.058	0.105***
	(0.355)	(0.166)	(0.255)	(0.128)	(0.050)	(0.023)
Observations	2,141	2,537	2,141	2,537	2,141	2,537

Notes: Standard errors are bootstrapped (1,000reps) and clustered at the firm level; *** p<0.01, ** p<0.05, * p<0.1. Control variables include occupation dummies, a dummy for being married and firm characteristics, tenure and its square are also included in the current wage regressions.

Table 10: Determinants of the within-firm hiring channel wage gap

Within-firm wage gap	(1)	(2)
Education	-0.001	0.014
	(0.041)	(0.043)
Finance	0.029	0.050
	(0.055)	(0.053)
Manufacturing	-0.022	-0.017
	(0.041)	(0.043)
Pub Admin	0.014	0.013
	(0.045)	(0.047)
21-70 employees	-0.051	-0.040
	(0.037)	(0.036)
71 or more employee	-0.070*	-0.060
	(0.040)	(0.041)
Formal performance review	0.038*	0.018
	(0.023)	(0.024)
Informal networks main hiring channel	-0.014	0.003
	(0.032)	(0.039)
Firm exports	0.061*	0.054
	(0.036)	(0.039)
Firm provides OTJ training	0.012	0.026
	(0.034)	(0.036)
Percent of top mgmt females	-0.020	-0.052
	(0.077)	(0.091)
Female manager	0.023	-0.005
	(0.053)	(0.061)
Manager college educated	-0.025	-0.044
	(0.041)	(0.048)
Communication skills		0.033*
		(0.019)
Team work skills		-0.028
		(0.023)
Problem solving skills		-0.020
		(0.022)
Literacy skills		-0.042*
		(0.022)
Numeracy skills		0.010
		(0.017)
Customer care skills		-0.009

		(0.014)
Responsibility		0.016
		(0.023)
Motivation		0.001
		(0.026)
Creativity		0.006
		(0.025)
Vocational job-specific skills		0.011
		(0.019)
Importance in hiring decision for professionals:		
Academic performance		0.031*
		(0.017)
Work experience		-0.002
		(0.025)
Skill set		0.007
		(0.024)
Interview		-0.029**
		(0.015)
Informal network/recommendation		0.016
		(0.040)
Political affiliation		0.002
		(0.042)
Constant	0.459***	0.469***
	(0.058)	(0.060)
Observations	171	171
R^2	0.081	0.176

Source: Standard errors are bootstrapped (1,000reps) and clustered; *** p<0.01, ** p<0.05, * p<0.1. The base outcomes are: commerce (industry) and firms with up to 20 employees (firm size).

Figure A1: Current wage by hiring channel

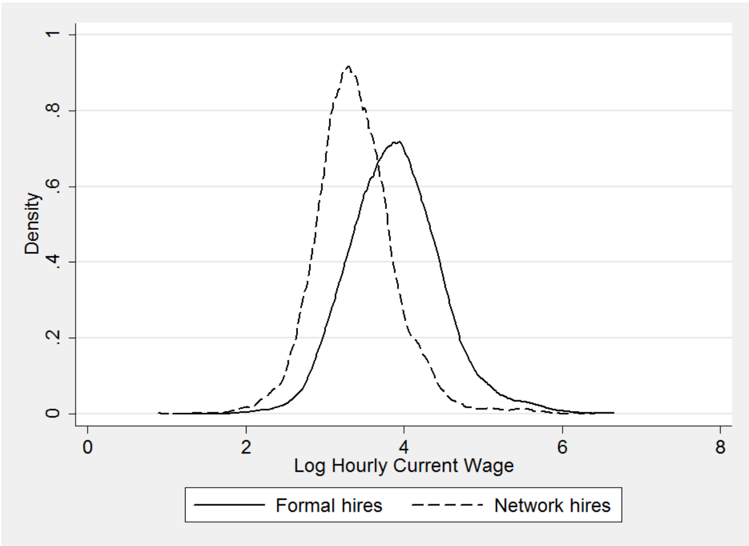

Figure A2: Current wage by detailed hiring channel

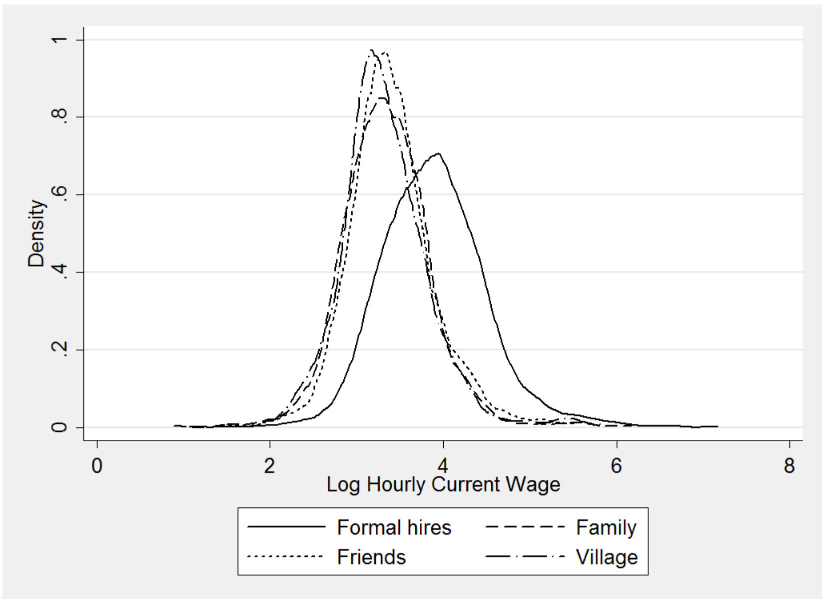

Figure A3: Current wage by hiring channel

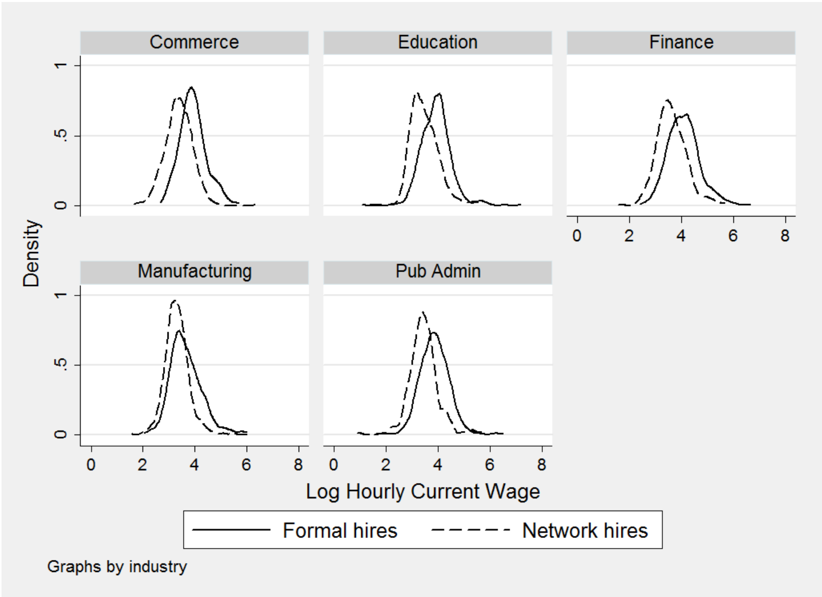

Table A1: Correlations between the skills measures

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Years of education	-								
(2) Reading score	0.75***	-							
(3) Numeracy score	0.50***	0.60***	-						
(4) Extraversion	-0.02	-0.00	-0.10***	-					
(5) Openness to Experience	0.09***	0.12***	0.11***	0.06	-				
(6) Conscientiousness	0.10***	0.15***	0.18***	0.02	0.36***	-			
(7) Emotional Stability	-0.04***	-0.05**	-0.04	-0.29***	-0.30***	-0.21***	-		
(8) Agreeableness	0.09***	0.11***	0.15***	-0.00	0.35***	0.36***	-0.26***	-	
(9) Hostile attribution bias	0.02	0.02	0.04***	0.17***	0.25***	0.18***	-0.34***	0.28***	-
(10) Grit	0.09***	0.13***	0.17***	0.09***	0.36***	0.42***	-0.27***	0.37***	0.29***

Notes: The value in each cell is the pairwise correlation; *** = $p < 0.01$; N = 4,678.

Table A2: Characteristics of employees by sex

Employees	All	Men	Women
Log Hourly Current Wage	3.62	3.89	3.39
	(0.61)	(0.59)	(0.51)
Married	0.77	0.83	0.72
	(0.42)	(0.37)	(0.45)
Age	31.68	33.30	30.31
	(8.38)	(8.10)	(8.37)
Age at hiring	26.04	26.88	25.33
	(6.47)	(5.86)	(6.86)
Previous experience (years)	1.98	1.94	2.02
	(3.11)	(3.15)	(3.07)
Tenure (years)	5.63	6.42	4.97
	(5.66)	(6.24)	(5.02)
Manager	0.05	0.05	0.06
	(0.22)	(0.22)	(0.23)
Skilled white collar	0.55	0.76	0.38
	(0.50)	(0.43)	(0.48)
Skilled blue collar	0.27	0.10	0.41
	(0.44)	(0.30)	(0.49)
Unskilled	0.13	0.09	0.16
	(0.34)	(0.29)	(0.37)
Lives in capital (Dhaka)	0.59	0.51	0.65
	(0.49)	(0.50)	(0.48)
Reading score	4.62	5.99	3.45
	(2.60)	(2.02)	(2.47)
Numeracy score	5.71	6.36	5.16
	(2.01)	(1.66)	(2.11)
Extraversion	6.43	6.41	6.45
	(1.58)	(1.56)	(1.59)
Openness to experience	7.52	7.68	7.39
	(1.89)	(1.95)	(1.83)
Conscientiousness	7.53	7.65	7.44
	(1.86)	(1.91)	(1.81)
Emotional stability	7.75	7.65	7.84
	(1.86)	(1.90)	(1.82)
Agreeableness	7.34	7.45	7.26
	(1.96)	(1.98)	(1.94)
Hostile attribution bias	4.29	4.38	4.22
	(1.66)	(1.65)	(1.66)
Grit	7.45	7.60	7.32
	(1.87)	(1.90)	(1.83)
Primary schooling	0.31	0.07	0.50
	(0.46)	(0.26)	(0.50)
Secondary schooling	0.46	0.49	0.43
	(0.50)	(0.50)	(0.50)
Tertiary schooling	0.23	0.44	0.06
	(0.42)	(0.50)	(0.24)
Found job through network	0.54	0.00	1.00
	(0.50)	(0.00)	(0.00)
Observations	5,330	4,678	652

Notes: Sample excludes employees for whom personality questions are missing (about 16 percent). Maximum score for literacy and numeracy is 8. Maximum score for the personality trait variables is 12. Standard deviation in brackets.

Table A3: Returns to skills using education dummies

Variables	(1)	(2)	(3)
Primary school education	0.034	0.025	0.008
	(0.029)	(0.029)	(0.028)
Junior secondary education	0.151***	0.134***	0.090***
	(0.032)	(0.033)	(0.032)
Secondary education	0.344***	0.317***	0.232***
	(0.036)	(0.040)	(0.036)
Higher secondary education	0.492***	0.457***	0.329***
	(0.038)	(0.043)	(0.042)
Vocational education	0.687***	0.650***	0.454***
	(0.063)	(0.068)	(0.065)
Post-secondary education (diploma)	0.824***	0.793***	0.570***
	(0.068)	(0.072)	(0.076)
Bachelor	0.859***	0.820***	0.603***
	(0.040)	(0.048)	(0.053)
Post-graduate (Master, Doctor)	1.133***	1.094***	0.837***
	(0.049)	(0.056)	(0.061)
Prior experience	0.024***	0.025***	0.018***
	(0.006)	(0.006)	(0.005)
Prior experience (sqrd)	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Tenure in current firm	0.031***	0.031***	0.029***
	(0.004)	(0.004)	(0.004)
Tenure in current firm (sqrd)	-0.001***	-0.001***	-0.000***
	(0.000)	(0.000)	(0.000)
Married	0.102***	0.106***	0.113***
	(0.021)	(0.021)	(0.021)
Reading score		0.006	0.007
		(0.006)	(0.006)
Numeracy score		0.000	-0.000
		(0.008)	(0.008)
Extraversion		0.018	0.018*
		(0.011)	(0.010)
Openness to Experience		0.007	0.001
		(0.011)	(0.010)
Conscientiousness		0.009	0.006
		(0.010)	(0.010)
Emotional Stability		0.013	0.014
		(0.011)	(0.010)
Agreeableness		0.006	0.007
		(0.010)	(0.010)
Hostile Attribution bias		-0.000	-0.001
		(0.010)	(0.009)
Grit		-0.009	-0.017*
		(0.010)	(0.010)
Firm characteristics			YES
Occupation dummies			YES
Constant	2.971***	2.959***	3.035***
	(0.037)	(0.051)	(0.121)
Observations	4,678	4,678	4,678
R^2	0.470	0.472	0.515

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1; Omitted category for the education dummies is category 1, *no school/incomplete primary school.*

Table A4: Correlations between occupations and hiring channels

	Hiring channel				
Occupation	Formal	Family	Friends	Village	Politics & School
Managers	-0.02	0.02	-0.00	-0.00	-0.01
Professionals	0.28***	-0.14***	-0.13***	-0.08***	-0.02
Technicians and associate professionals	-0.00	-0.02	0.02	0.01	-0.00
Clerical support workers	0.20***	-0.08***	-0.09***	-0.10***	-0.01
Service workers	0.08***	-0.03	-0.07***	0.00	0.01
Sales workers	-0.03	0.03	0.02	-0.02	-0.01
Skilled agricultural	0.01	0.03	-0.03	-0.01	-0.01
Construction, craft, and related trade	-0.32***	0.12***	0.17***	0.13***	0.00
Plan and machine operators, assemblers	-0.11***	0.07***	0.06***	-0.01	0.00
Elementary occupations	-0.10***	0.04***	0.03	0.05***	0.04***

Notes: The value in each cell is the pairwise correlation; *** = $p < 0.01$; N = 4,678.

Table A5: Returns to skills

Log hourly wages	(1) Formal	(2) Formal	(3) Networks	(4) Networks
Years of education	0.013	0.009	-0.028***	-0.029***
	(0.018)	(0.016)	(0.009)	(0.009)
Years of education (sqrd)	0.003***	0.002***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Prior experience	0.033***	0.024***	0.019**	0.014*
	(0.008)	(0.008)	(0.008)	(0.007)
Prior experience (sqrd)	-0.000**	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current firm	0.024***	0.025***	0.036***	0.032***
	(0.006)	(0.005)	(0.005)	(0.005)
Tenure in current firm (sqrd)	-0.000	-0.000*	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Reading score	0.048*	0.052**	-0.000	0.000
	(0.025)	(0.025)	(0.018)	(0.018)
Numeracy score	-0.024	-0.031	0.011	0.011
	(0.024)	(0.023)	(0.018)	(0.017)
Married	0.099***	0.097***	0.101***	0.113***
	(0.031)	(0.031)	(0.026)	(0.027)
Extraversion	0.027*	0.033**	0.011	0.007
	(0.015)	(0.013)	(0.014)	(0.013)
Openness to Experience	0.029**	0.020	-0.013	-0.015
	(0.014)	(0.013)	(0.015)	(0.014)
Conscientiousness	0.003	0.000	0.015	0.010
	(0.014)	(0.015)	(0.014)	(0.013)
Emotional Stability	-0.001	0.001	0.029**	0.029**
	(0.014)	(0.014)	(0.014)	(0.013)
Agreeableness	0.004	0.003	0.007	0.008
	(0.013)	(0.013)	(0.014)	(0.014)
Hostile Attribution bias	-0.015	-0.018	0.009	0.011
	(0.014)	(0.013)	(0.013)	(0.013)
Grit	-0.020	-0.025*	-0.003	-0.013
	(0.016)	(0.015)	(0.012)	(0.011)
Firm characteristics		YES		YES
Occupation dummies		YES		YES
Constant	2.934***	3.060***	2.996***	3.213***
	(0.107)	(0.156)	(0.052)	(0.116)
Observations	2,141	2,141	2,537	2,537
R^2	0.416	0.481	0.318	0.372

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Differentiated returns to skills by tenure

	Tenure: 0-4 years		Tenure: 5+ years	
Log hourly wages	Formal	Networks	Formal	Networks
Years of education	-0.000	-0.029**	-0.098**	-0.030*
	(0.026)	(0.013)	(0.040)	(0.016)
Years of education (sqrd)	0.002	0.003***	0.006***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Prior experience	0.050***	0.002	0.001	0.013
	(0.017)	(0.010)	(0.013)	(0.016)
Prior experience (sqrd)	-0.001	0.001	0.000	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)
Reading score	0.018	-0.014	0.001	-0.023
	(0.036)	(0.025)	(0.047)	(0.035)
Numeracy score	-0.030	0.011	-0.005	0.017
	(0.029)	(0.020)	(0.032)	(0.021)
Extraversion	0.032*	0.008	0.031*	0.012
	(0.017)	(0.015)	(0.017)	(0.021)
Openness to Experience	0.025	-0.014	0.019	-0.029
	(0.017)	(0.016)	(0.021)	(0.019)
Conscientiousness	0.002	0.009	0.003	0.015
	(0.022)	(0.017)	(0.020)	(0.020)
Emotional Stability	-0.010	0.035**	0.014	0.002
	(0.019)	(0.015)	(0.020)	(0.018)
Agreeableness	0.007	0.013	0.003	0.002
	(0.017)	(0.017)	(0.018)	(0.019)
Hostile Attribution bias	-0.029*	0.002	-0.011	0.019
	(0.017)	(0.016)	(0.019)	(0.019)
Grit	-0.019	-0.019	-0.051***	-0.020
	(0.020)	(0.017)	(0.019)	(0.016)
Firm characteristics	YES	YES	YES	YES
Occupation dummies	YES	YES	YES	YES
$\rho 1$	-0.484*	-0.744	-0.887***	0.457
	(0.271)	(0.615)	(0.304)	(0.561)
$\rho 2$	0.242	0.542	0.022	0.597*
	(0.433)	(0.385)	(0.480)	(0.344)
Constant	3.535***	3.319***	4.394***	3.489***
	(0.258)	(0.167)	(0.421)	(0.180)
Observations	1,162	1,574	979	963

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Characteristics of firms used in wage gap analysis sample

Percentage of firms	Original	Restricted
At most 20 employees	37.9	17.0
21 - 70 employees	23.4	28.7
More than 70 employees	38.7	54.4
Commerce	14.9	15.8
Education	15.1	18.7
Finance	39.9	15.2
Manufacturing	39.9	40.9
Public administration	15.1	9.4
Firm located in Dhaka	52.6	64.9
Main channel of job advert: networks	33.7	19.9
One channel of job advert: networks	53.8	48.5
Total number of firms	496	171

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS). Restricted sample are firms with at least 2 formal and 2 network male workers.

Table A8: Characteristics of employees - original versus original sample

Employees	Original	Restricted		
		All	Formal Hires	Network Hires
Log Hourly Current Wage	3.62	3.64	3.85	3.44
	(0.61)	(0.60)	(0.60)	(0.52)
Age	31.68	31.23	32.20	30.23
	(8.38)	(8.06)	(7.67)	(8.31)
Age at hiring	25.96	25.69	26.45	24.95
	(6.45)	(6.10)	(5.71)	(6.38)
Previous experience (years)	1.98	1.96	1.98	1.93
	(2.99)	(2.93)	(2.97)	(2.89)
Tenure (years)	5.63	5.53	5.77	5.30
	(5.62)	(5.42)	(5.39)	(5.44)
Manager	0.05	0.05	0.06	0.04
	(0.22)	(0.22)	(0.24)	(0.19)
Skilled white collar	0.55	0.57	0.72	0.42
	(0.50)	(0.50)	(0.45)	(0.49)
Skilled blue collar	0.27	0.25	0.14	0.36
	(0.44)	(0.43)	(0.35)	(0.48)
Unskilled	0.13	0.13	0.07	0.18
	(0.35)	(0.33)	(0.26)	(0.39)
Lives in capital (Dhaka)	0.58	0.67	0.63	0.72
	(0.49)	(0.47)	(0.48)	(0.45)
Reading score	4.62	4.94	5.93	3.97
	(2.63)	(2.48)	(2.10)	(2.44)
Numeracy score	5.71	5.86	6.35	5.39
	(2.02)	(1.98)	(1.68)	(2.12)
Extraversion	6.36	6.40	6.35	6.45
	(1.58)	(1.57)	(1.57)	(1.57)
Openness to Experience	7.46	7.56	7.68	7.45
	(1.89)	(1.85)	(1.87)	(1.82)
Conscientiousness	7.57	7.60	7.60	7.60
	(1.84)	(1.86)	(1.88)	(1.85)
Emotional Stability	7.85	7.74	7.69	7.79
	(1.87)	(1.84)	(1.85)	(1.84)
Agreeableness	7.25	7.48	7.53	7.43
	(2.00)	(1.90)	(1.91)	(1.89)
Hostile attribution bias	4.29	4.42	4.43	4.41
	(1.66)	(1.59)	(1.59)	(1.60)
Grit	7.45	7.56	7.67	7.46
	(1.87)	(1.89)	(1.89)	(1.90)
Primary schooling	0.31	0.23	0.09	0.37
	(0.46)	(0.42)	(0.28)	(0.48)
Secondary schooling	0.46	0.51	0.50	0.53
	(0.50)	(0.50)	(0.50)	(0.50)
Tertiary schooling	0.24	0.25	0.41	0.10
	(0.43)	(0.44)	(0.49)	(0.29)
Found job through informal network	0.54	0.51	0.00	1.00
	(0.50)	(0.50)	(0.00)	(0.00)
Observations	4,678	2,525	1,242	1,283

Notes: Restricted sample are workers in firms with at least 2 formal and 2 network male workers. Sample excludes employees for whom personality questions are missing (about 16 percent). Maximum score for literacy and numeracy is 8. Maximum score for the personality trait variables is 12. Standard deviation in brackets.

Figure A4: Within firm wage gap by industry