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ABSTRACT

Cognitive and Non-Cognitive Skills, Hiring Channels, and Wages in Bangladesh*

This paper uses a novel matched employer-employee data set representing the formal sector in Bangladesh to provide descriptive evidence of both the relative importance of cognitive and non-cognitive skills in this part of the labor market and the interplay between skills and hiring channels in determining wages. While cognitive skills (literacy, a learning outcome) affect wages only by enabling workers to use formal hiring channels, they have no additional wage return. Non-cognitive skills, on the other hand, do not affect hiring channels, but they do enjoy a positive wage return. This wage return differs by hiring channel: those hired through formal channels benefit from higher returns to openness to experience, but lower returns to conscientiousness and hostile attribution bias. Those hired through networks enjoy higher wages for higher levels of emotional stability, but they are also punished for higher hostile attribution bias. This is in line with different occupational levels being hired predominantly through one channel or the other. We provide suggestive evidence that employers might use hiring channels differently, depending on what skill they deem important: employers valuing communication skills, a skill that could arguably be observed during selection interviews, are associated with a larger within-firm wage gap between formal and network hires, while the importance of teamwork, a skill that is more difficult to observe at the hiring stage, is associated with a smaller wage gap.

JEL Classification: J24, J31, J71, O12

Keywords: cognitive skills, personality traits, networks, matched worker-firm data, Bangladesh

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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 that extend beyond cognitive ability.

Non-cognitive skills are likely to have both direct and indirect effects 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., 2015). Literature so far has focused on developed countries and oftentimes on either direct or indirect effects alone. Little research has been done regarding wage returns to non-cognitive skills in developing countries, which are likely to be different. Employers in developing countries might, for example, reward skills that deal with the precise execution of tasks (such as being conscientious and emotionally stable) more than 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 cognitive and 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 skills on wages. To our knowledge, no paper has so far considered both the direct and indirect effect of cognitive and non-cognitive skills on wages, especially in a developing country context. This paper does both, first looking at the effect of cognitive and non-cognitive skills on hiring channels chosen and then estimating outcomes of the job search and returns to wages for those skills, given the initial selection into hiring channels.[1]

The cognitive skills included are measured by numeracy and literacy tests. These cognitive skills are not 'pure' cognitive skills in the sense of capturing only intelligence. Instead, they are learning outcomes, capturing levels of intelligence needed to accomplish a task as well as the effort on that task and motivation to complete it. As such, they are an imperfect measure of pure cognitive skills, but they are the only measure available in the data set and have been used as proxies in the literature (Hanushek and Woessmann, 2008). The non-cognitive skills considered are measured by the Big Five personality test (openness to experience, conscientiousness, extraversion, agreeableness, and emotional stability); a set of socio-emotional skills (hostile attribution bias and grit) is also included. All are based on a self-assessed questionnaire. Given the nature of the survey (a matched employer-employee data set) we are able to include firm fixed effects, which allows us to account for firm-specific heterogeneity in rewarding certain skills. Additionally, we explore demand-side preferences for specific skills by decomposing within-firm wage gaps between workers who have been hired through formal channels and those hired through networks to better understand whether those gaps are driven by firm characteristics or preferences for certain skills.

The survey covers the formal sector, which is the sector that will contribute most strongly to the shift from agriculture into higher skilled sectors in Bangladesh. While most 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). Still, formal sector employment in Bangladesh represented only about 11.5 percent of total employment in 2010 (Asian Development Bank and Bangladesh Bureau of Statistics, 2012). While our results are thus

[1]The idea of the paper is to endogenize the hiring channel. We certainly admit that other choices could be endogenous as well, e.g. job choice or task choice; however, this paper deliberately decided to only look at the hiring channel.

only applicable to this small share of the Bangladeshi labor market, our paper still contributes to a better understanding of which skills are required in the part of the labor market likely to be the primary driver of faster GDP growth and poverty reduction.

We find that non-cognitive skills do not affect the selection of the hiring channel, but they do have a direct effect on wages, after correcting for initial selection. These significant correlations are not visible in simple OLS regressions and differ by hiring channel; they therefore illustrate the benefit of first taking into account selection into different hiring channels. For those hired formally, the wage returns to an additional standard deviation of openness to experience is 2.5 percent. However, not all non-cognitive skills benefit from positive wage returns: those hired formally are punished for having higher levels of conscientiousness and hostile attribution bias. Looking at differential results by occupation shows that the result for conscientiousness is driven by white collar workers, among whom other traits, such as creativity or flexibility are arguably more important than diligently completing tasks. Among those hired through networks, hostile attribution bias also shows a negative wage return. Network hires can benefit from a positive return to emotional stability though with a one standard deviation increase in the trait associated with a 1.9 percent wage increase. These are considerable returns, especially when compared to average returns to education in developing countries. Returns to skills thus seem to align with the task content of work.

We then explore the demand side to understand whether firm characteristics and preferences for certain skills can help explain differential returns to skills. We find that employers who value communication skills more are associated with a larger within-firm wage gap between formal and network hires, while those who value teamwork more are associated with a smaller wage gap, though this result only holds for professional workers, such as managers or technicians. We explain this result through the firm's decision to hire through different channels among highly skilled workers. If the employer values communication skills, they will choose a hiring channel that allows them to observe these skills. As communication skills can arguably be well observed during formal interviews, this increases the wage gap between formal and informal hiring. Teamwork skills, on the other hand, might be more difficult to observe reliably in a simple job interview, which is why firms valuing these skills might rely more on networks to provide otherwise unobservable information about a worker. This mechanism only seems to hold for professional workers; among non-professional workers, other mechanisms, such as firms hiring through networks to overcome moral hazard problems of workers shirking, as observed in Heath (2018), could dominate.

The nature of this paper is purely descriptive, as the data do not allow us to draw any causal inferences. Still, we believe that it is valuable to engage in a descriptive analysis given the lack of information on returns especially to non-cognitive skills in a developing country setting. Further, to our best knowledge, no paper has previously examined the potential interplay between hiring channels and non-cognitive skills, a factor that could be of particular importance in a developing country, in which hiring through networks is very prevalent.

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 our results, and section 6 concludes.

2 Literature and conceptual framework

2.1 Literature review

The impact of education and experience on wages has been widely discussed since the seminal work of Becker (1964) and Mincer (1974).[2] Still, focusing solely on returns to education ignores the innate multidimensionality of human capital, which combines cognitive ability and non-cognitive skills. Lack of data has meant that cognitive and non-cognitive skills have been oftentimes part of the unobservable.

Cognitive skills are often approximated via standardized test scores in developed countries or literacy and numeracy tests in developing countries. Hanushek and Woessmann (2008) provide 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. Still, it is important to note that cognitive skills measured by numeracy and literacy are less of a measure of true cognitive ability than other instruments, such as Raven's Progressive Matrices. 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 smaller on average than in the US. In developing countries, Lee and Newhouse (2012) find that higher cognitive ability is associated with measures of better job quality.[3]

Non-cognitive skills such as 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; Heineck and Anger, 2010), and to be a predictor of labor market outcomes (Borghans et al., 2008). Mueller and Plug (2006) show that the effect of personality traits on earnings is of a similar magnitude to that of cognitive skills. In the framework of the Big Five, conscientiousness (Nyhus and Pons, 2005) and emotional stability (Drago, 2011) have been linked to better job performance and higher wages. Recently, "grit", perseverance in the pursuit of 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 important than, or at least as important as, actual talent.

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. Other papers have found rather mixed evidence: Glewwe et al. (2017) show that, in China, both cognitive and non-cognitive skills are important for the school-to-work transition, but they do not predict wages; similarly, Acosta et al. (2015)

[2] 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.

[3] Assessing the differential impacts of years of schooling and cognitive skills on labor market outcomes is not without problems, since including intelligence tests 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. (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.

find a larger impact of cognitive than non-cognitive skills on labor market outcomes; and OECD (2015) suggests that raising cognitive skills might ultimately be more important than raising socio-emotional skills in determining incomes. However, recent intervention aimed at improving non-cognitive skills shown some success, such as among adolescents in India (Krishnan and Krutikova, 2013).

This discussion shows that personality traits have both a direct and an indirect impact on wages by determining, for instance, labor market participation, the school-to-work transition, or formality status. In this paper, we are focusing on one indirect factor: the use of social networks in the hiring process. If individuals self-select into different channels of job search depending on their human capital, the hiring channel could then mitigate wage returns to skills. This is particularly important in developing countries, where formal institutions are traditionally weak and social networks are employed frequently in job searches (Fafchamps, 2006). Social networks have been found to both increase and decrease wages as outlined below.

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 (e.g. Kugler, 2003; Simon and Warner, 1992). Burks et al. (2015) look at employee referrals in three industries (call centers, trucking, and high-tech) and find that workers who obtained their jobs through employee referral earn slightly higher wages and have lower turnover and recruiting costs. Heath (2018) examines the garment sector in Bangladesh, in which jobs are rarely formally published. She finds that firms use referrals to mitigate the moral hazard problem by being able to punish referrers if they refer an unproductive worker.

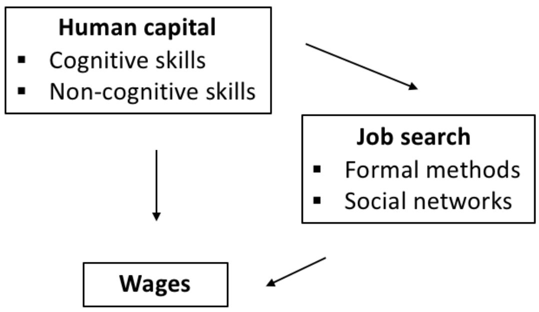
Having to use social networks to find a job can also be perceived as a negative signal to employers, however, as those relying on networks might simply be workers in greater need of a job of any sort (Granovetter, 1995). If the latter channel is at work, workers searching for jobs via social networks exhibit a lower reservation wage, suggesting that finding a job through a social network will thus be negatively related to wages. Empirical evidence can also be found in support of a negative relationship between social network job search and wages (e.g. Bentolila et al., 2010; Berardi, 2013).

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, 2016). Human capital has been found to affect network formation. 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) similarly have access to larger and more diverse social networks (Pollet et al., 2011; Wu et al., 2008). Caliendo et al. (2015) further show that non-cognitive skills also influence job search as individuals with an internal locus of control exert higher search effort.

2.2 Conceptual framework

The literature demonstrates that cognitive and non-cognitive skills are likely to have a direct and an indirect effect on wages. The direct effect of non-cognitive skills stems from personality being considered part of a worker's endowment, which is rewarded directly by the employer if this 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 intensity of job search (Caliendo et al., 2015). This paper combines the direct and indirect effects by first looking at the effect of cognitive and non-cognitive skills on hiring channels chosen and then estimating outcomes of the job search and returns to wages for those skills, given the initial selection into hiring channels (Figure 1).

Figure 1 – Conceptual framework illustrated



Non-cognitive skills in our paper are captured by the Big Five framework of personality traits. The Big Five are a widely used list of key traits, which are understood to capture the broadest level of personality traits.[4] The Big Five framework includes: (1) openness to experience, which captures one's tendency to be open to new experiences (aesthetic, cultural or intellectual); (2) conscientiousness, one's tendency to be organized, hardworking, and responsible; (3) extraversion, directing one's interest towards the outer world of people and things; (4) agreeableness, the tendency to act cooperatively and in an unselfish manner; and (5) emotional stability, predictability and consistency in emotional reactions with absence of rapid mood changes. 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 systematic bias which leads to individuals interpreting the ambiguous behavior of others as hostile towards them.

To illustrate the conceptual framework, assume that a worker is very agreeable. Individuals who score highly on this personality trait are usually considerate, generous, willing to compromise their interests with those of others, and likely to have a larger and closer group of friends. Thus, we assume that scoring more highly on agreeableness increases a worker's probability of finding a job through friends or other social connections. On the job, agreeableness is perceived as positive, especially in teamwork settings. However, agreeable individuals are also likely to compromise their interests with those of others – not necessarily a valued tendency on the workplace. In

[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).

terms of wage returns, the trait agreeableness could then first have an indirect effect on wages purely through enabling network hiring (positive or negative). In addition, agreeableness could have a direct effect on wages (positive or negative) depending on how well the trait enables the individual to perform his job.

Considering both direct and 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, 2010). Similarly, we expect cognitive skills to have a positive effect on the probability of having found the job through formal channels. People who are more extroverted, more outgoing, and take on more leadership roles have access to larger social networks and might thereby receive more information and offers through the network, increasing their likelihood of finding a job through their network. As mentioned in the example above, we assume agreeableness to have a positive effect on network hiring. The effect of conscientiousness, which has been linked to hard work and strong self-control, and emotional stability, which has been associated with better task performance, is unclear. On the one hand, friends or family might be more willing to provide a recommendation for a hard worker, increasing hiring through networks. On the other hand, the worker might prefer to opt for formal, official hiring channels instead of back-doors. Grit refers to perseverance in pursuit of long-term goals. 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 of finding a job through networks.

Regarding 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 to be positive and significant. Literature on wage returns to the traits of the Big Five framework in developing countries is scarce. In developed countries, the literature has found positive effects for conscientiousness, extraversion, emotional stability, and grit on career success (Duckworth et al., 2007; Judge et al., 1999). Conscientiousness and grit quite naturally coincide with professional success, extraversion can be especially useful in a business environment and emotional stability enables performance on specific tasks. Hostile attribution bias is assumed to have a negative effect on wages, but 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 in jobs for which strict obedience and subordination are, on the contrary, highly expected from employees. Similarly, agreeableness coincides with being more likable and cooperative, which is beneficial in a teamwork setting, but might be a hindrance if the worker places his co-workers' interests above his own.

3 Data

This paper is based on the 2012 Bangladesh Enterprise-Based Skills Survey (ESS), a matched employer-employee survey commissioned by the World Bank with the aim of assessing whether the educational system in Bangladesh is producing graduates with skills relevant to and demanded by firms (Nomura et al., 2013).[5] The survey covers formal sector firms in the industrial and manufacturing sectors. Most of Bangladeshi employment occurs in the informal sector; it is therefore important to note that results from this data only hold for a rather selected sample of workers. In particular, the 2010 Bangladeshi Labor Force Survey (the survey closest to this data

[5]Two authors of this paper were part of the team designing and implementing the survey.

set) shows that only 11.5 percent of employment in Bangladesh occurs within the formal sector (Asian Development Bank and Bangladesh Bureau of Statistics, 2012). This share is slightly higher among men (13.2 percent), but it remains low. While the formal sector employment grew to 14 percent of total employment in 2016, it remains small on a global scale. Additionally, workers in formal firms are likely to be selected, due to better working conditions and wages in formal firms. In Bangladesh, the incidence of informal employment decreases with educational attainment (World Bank, 2018). For example, only 3.7 percent of employed Bangladeshi men have a high school degree and another 4.2 percent obtained a Bachelors degree, but their shares among formal workers are 10.6 and 18.7 percent, respectively (Asian Development Bank and Bangladesh Bureau of Statistics, 2012).

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 its limitation to five sectors, the survey is quite representative, as these sectors cover 87 percent of formal sector enterprises and 91 percent of total formal sector employment in Bangladesh (Nomura et al., 2013). Thus, the data used in this study only allow us to draw conclusions about a small part of the Bangladeshi labor market; still, conclusions drawn for the formal sector are representative.

The survey unit of the ESS is the firm; the survey consists of two modules, one each for employees and employers. The employee part of the survey is conducted for a sub-sample of employees in the sampled firms.[6] It contains detailed information of each individual's background, educational attainment, and numeracy and literacy skills, as well as their personality traits. 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. Again, the sample of workers in formal firms is on average much more educated than the population in general. According to the labor force survey, only 14.1 percent of all formal sector workers in 2010 did not complete primary education (Asian Development Bank and Bangladesh Bureau of Statistics, 2012). The test level thus seems highly appropriate and the test is administered to all workers, regardless of whether or not they have completed primary education. Personality measures are based on the Big Five typology of personality tests, with the short Big Five Inventory (BFI-S) included in the survey. It was originally developed by John and Srivastava (1999) and has been validated in large panel surveys such as the German Socio-Economic Panel Survey (McCrae and Costa, 2008).

The employee survey also asks workers to elicit information about their job search process. The question was asked in a nested way. First, workers are asked how they found their current job. Answer possibilities include media advertisement/posting, informal networks (including a reference from somebody), a school, public employment services, private employment services, job fairs, internet posting, and others (specify). Second, those who replied "informal networks" where then subjected to a follow-up question that inquired which informal network was used. Answer possibilities include family/relatives, friends, political affiliation, school alumni, and same village/town. For the remainder of this paper, all workers who said they used a job search method other than "informal networks" will be classified as having found their job through "formal channels". Those who replied informal networks and answered the follow-up question on what type of network they used will be classified as having found their job through "networks".

Responses for the employer module come from business owners and high-level managers; its

[6]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).

questions deal with information on recruitment and training of employees, as well as an assessment of the workplace, and firm performance. It contains information on senior management itself (such as gender and 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 problem solving, motivation, or their ability to work as part of a team).

4 Methodology

Our methodological approach consists of estimating different models to assess the impact of cognitive and non-cognitive skills on wages and the choice of the hiring channel. We restrict our sample to male workers with non-missing skills variables, since men and women might differ in their endowment of non-cognitive skills (Fortin, 2008) or the same personality trait might be valued differently by employers according to gender (Heineck and Anger, 2010). Nordman et al. (2015) find that personality traits reduce the male-female wage gap in the upper part of the wage distribution using the same data set as this paper.[7]

We start from Mincer-type wage regressions and take into account the indirect effects of the use of networks through bimodal 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 within the same firm. We decompose this observed within-firm wage gap to understand whether it is driven by firm characteristics or skill preferences.

4.1 Returns to skills

Our basic model is a simple Mincer specification:

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

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, total work experience, and a dummy for being married. Returns to education are likely to be non-linear, especially in developing countries (Kuépié et al., 2009; Söderbom et al., 2006), which we capture with a simplified model using a low-order polynomial (Card, 1999). We further introduce controls for occupation, as Heckman et al. (2006) have shown that individuals sort into occupations and education based on their personality traits, meaning our estimate of returns to personality could be overestimated if it simply captures occupational effects. *Cog* includes individual i's cognitive skills, the standardized score of the worker on the numeracy and literacy tests, and *NonCog* his non-cognitive skills, the standardized scores of each dimension of the Big Five personality assessment and the standardized scores of the socio-emotional skills grit and hostile attribution bias. δ_j captures firm fixed effects to capture the effect that firm-level determinants of wages might have on wage setting (Abowd et al., 1999; Groshen, 1991).

The non-cognitive skills data in the survey suffer from a large amount of missing values. We therefore only keep individuals who answered at least two out of the three questions per dimension.[8] We then correct the items for acquiescence,[9] before assessing the internal validity of

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

[8] This reduces our sample from 6,092 men to 4,678 men. We thus lose about 23 percent of the raw sample.

[9] Acquiescence refers to a response bias in the form of being more likely to agree or disagree with questions

each trait by computing Cronbach's α. Correcting for acquiescence improves the internal validity for all constructs except for grit, for which it decreases validity substantially (from 0.22 to 0.09). We therefore keep the raw grit dimension and use acquiescence corrected version for the other skills. The threshold for good validity is $\alpha \geq 0.7$. None of our dimensions reach that threshold, but several come close. In ascending order, the αs are: 0.22 (grit), 0.33 (hostile attribution bias), 0.34 (agreeableness), 0.42 (openness to experience), 0.45 (extraversion), 0.61 (emotional stability), and 0.63 (conscientiousness).[10] The internal validity of our constructs is therefore not ideal and implies that results could suffer from measurement error, which would bias our results towards zero. We also consider creating scales based on the data and not our pre-defined dimensions, using exploratory factor analysis.[11] The three factors that can be retained from the data are a combination of emotional stability and extraversion (*Factor 1*), a combination of conscientiousness and grit (*Factor 2*) and a combination of agreeableness and openness to experience (*Factor 3*). This gives evidence to the observation that while one can theoretically distinguish between the different Big Five traits, in practice, they tend to be somewhat correlated. Due to the nature of the exploratory factor analysis, however, this approach reduces our sample size to those with non-missing skills variables only (N=3,102), which is why we stick to the Big Five distinction for most of the paper.

All 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 the true partial effect. Cognitive skills and 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).[12] Additionally, measurement error in both cognitive and non-cognitive skills is quite likely. Our estimates should therefore be interpreted as lower bounds.

In a second specification, we use starting wages at firm entry instead of current wages as our dependent variable. Starting wages have the advantage of having been set before an employer is intimately familiar with a given worker. It is especially interesting to see the effect of cognitive and non-cognitive skills on starting wages, since at this point in time the employer's information about workers consists only of observable information, such as experience and educational attainment, and knowledge received through the hiring channel (formal interviews, or information transmitted through a social network). If we find significant returns to some variable for current but not for starting wages, this suggests that effects are not spurious but stem from the employer learning about the worker's productivity and match to their job.

Pairwise correlations between skills and personality traits show small correlations between the different personality traits and cognitive skills, but significant correlations between the personality traits themselves (see Table A.1 in the Appendix). Our correlations are smaller than

in general.

[10]We also checked α only for those who have a complete non-missing non-cognitive questionnaire. This decreases our sample size to 3,102 but does not significantly improve α.

[11]We use Kaiser's criterion, Catell's scree plots, and Horn's parallel analysis (Cattell, 1966; Horn, 1965; Kaiser, 1958) to decide how many factors to retain, settling on 3 factors. We then rotate factor loadings using an oblique, olimin rotation to allow for latent factors to be correlated. Final factors are scored using regression scoring and standardized.

[12]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), which has also been shown in surveys (Cobb-Clark and Tan, 2011).

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 0.16. Still, they carry the expected sign (e.g. grit and conscientiousness correlate positively and significantly with numeracy). The correlation between cognitive factors and years of education attained is very large for literacy (0.75) and still quite substantial for numeracy (0.49); correlations between years of education and personality traits are small.

4.2 Skills and the type of hiring channel

OLS regressions provide our starting point, but they confound the direct and indirect effects that cognitive and non-cognitive skills have on wages, as they are unable to account for unobserved characteristics that influence the choice of hiring channel and could also influence wages that the worker receives once employed. More extroverted workers might have a higher probability of finding their job through networks such as friends and family, for example. Once employed, the worker's wage is influenced by having been hired through friends and networks (the indirect effect of extraversion). His wage will also be determined by the value the employer places on the worker's extraversion on the job (the direct effect).

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 bimodal and multinomial endogenous switching models.

Workers can be hired through formal channels or through networks. Each worker is only observed in one regime at a time, leading to the following two equations:

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

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

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

The switching regression then sorts individuals to one 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} is the 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 used networks as at least one of his potentially multiple channels of job search:

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

We are able to control for a wide range of characteristics at the worker and firm level. Still, workers searching through networks might differ from those searching through formal channels in their unobserved characteristics. 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 provides no such benefit. The individual would then benefit more from searching among his strongest ties instead, reaching out horizontally.

We introduce *mother has no formal education* as an identifying variable to approximate the aspect of network quality which could influence its usage. The data allow us to control for a worker's education, cognitive skills, and personality. Since these are able to control for almost all of the genetic factors that could correlate between a mother and her child (except possibly health), we believe that the only way a mother's education could have an effect on her child's wages is through providing access to differently shaped social networks, thus satisfying the exclusion restriction.[13] We further introduce *monthly household income* as an additional exclusion restriction to control for the fact that those from wealthier households might be able to bribe their way into jobs.

We estimate the switching model using, first a bimodal selection correction, distinguishing between workers hired formally or through social networks; we further attempt to use a multinomial selection correction, allowing for five different hiring channels (formal, family, friends, village, and political or school alumni organizations). Hausman and Small-Hsiao tests of Independence of Irrelevant Alternatives (IIA) assumption confirm that they are independent. Still, as we can only include firm characteristics and not firm fixed effects, we will place minimal emphasis on this additional distinction.[14]

[13] We also estimated the model using the formal education of the father and identifying the model by its functional form (without exclusion restriction). We opted for the formal education of the mother instead of the father because the latter was not a good predictor of hiring channel choice and an exclusion restriction is generally the preferred option. We further checked the robustness of the instrument for different subgroups (by educational attainment, levels of cognitive and non-cognitive skills), and occupational classification (blue/white collar). The instrument is robust for all subgroups except levels of educational attainment. Testing the instrument by levels of educational attainment shows that it only holds for those with medium levels of education (with the highest degree being either junior secondary school, secondary school, or high school). To us, this suggests the following within an instrumental variable framework: those with low levels of education search predominantly through social networks. The quality of the networks does not matter for them. Those with high levels of education predominantly search through formal channels, thus using mother's education as a proxy for the quality of the network is irrelevant for them. Those affected by the instrument in our case then are those with intermediate levels of education who might still search among family networks if those are of good quality (proxied by the level of formal education of the mother).

[14] The estimates that we provide based on a multinomial selection model rely on the selection correction developed in Bourguignon et al. (2007). Since a multinomial model with firm fixed effects was not converging, these models will use firm characteristics instead, which are industry, firm size, the sex of the top manager, and whether the firm exports.

5 Results

5.1 Descriptive statistics

For reasons outlined previously, we restrict our sample to male workers with non-missing non-cognitive skills variables. In total, we keep 4,678 male workers and 487 firms in our sample.[15] Table A.2 presents descriptive statistics of the firms in our sample.

The data include firms from five economic 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 in the Bangladeshi economy. Firms in commerce, education, and finance tend to be stand-alone companies, while firms in the manufacturing and public administration sectors typically belong to a larger (parent) company. Firms in the public administration sectors are almost all part of publicly owned organizations, though the picture is more mixed in the education sector, which is comprised of a mixture of government-owned, autonomously owned, and NGO-owned companies.[16] Public sector companies include a variety of economic activities, ranging from agriculture to administrative support and social work. Companies in the remaining sectors (commerce, finance, and manufacturing) are private enterprises or individually owned entities. Table A.2 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 about half the sample (54 percent), social networks are at least one of their hiring channels.

Table A.3 presents the characteristics of a random sample of employees within the sampled firms. Column (1) depicts means for the entire male sample. Workers surveyed are on average 32 years old. They were on average 26 years old at hiring at their current job and currently have about 6 years of work experience. The majority of workers are located in Dhaka, the capital of Bangladesh. 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 they score lowest on the acquiescence-corrected personality trait hostile attribution bias and highest on conscientiousness. Most workers are skilled white or blue collar workers, which can be explained by the rather specific sample of formal firms. A slight majority of workers obtained their current job via social networks (54 percent).

Comparing workers who found their job through formal job search methods (column (3)) and those who found their job through networks (column (5)) further reveals differences between the two groups. Workers who found their job through formal hiring channels earn higher wages on average. Figure A.1 illustrates that this wage gap persists over different economic sectors. Formally hired workers are slightly older, are more likely to work in skilled white-collar occupations (76 percent vs. 38 percent), and are less likely to live in Dhaka. Formally hired workers are more likely to be working on permanent contracts (96 percent), though even workers hired through networks predominantly have permanent contracts (86 percent).[17] They score higher on both

[15] By limiting our sample to male workers only, we lose about 12 percent of the original sample of workers and by limiting it to those with at least two answer per personality trait dimension, we lose an additional 23 percent of male workers. We further exclude 13 firms who did not have any male workers with non-missing skills variables. Our resulting sample is slightly better educated, slightly more likely to work in professional occupations, and slightly less likely to work in construction or elementary occupations.

[16] 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).

[17] We have some missing values for the contract type variable, hence the two different sample sizes in the table.

numeracy and literacy tests, are more educated (7 percent of the formal hires have obtained at most primary education compared to 50 percent of network hires), and are less conscientious, less extroverted, and less emotionally stable.[18]

5.2 Wage returns to different types of skills

5.2.1 Hourly wages

We estimate OLS regressions with the natural logarithm 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 Mincer type regressions, explaining wages as a function of human capital. The covariates included are years of education, total work experience[19], and quadratic effects for these two variables, as well as a dummy variable for being married. We add measures of cognitive ability (or, rather learning outcomes, based on standardized scores on numeracy and literacy tests) and non-cognitive traits (standardized values of the Big Five personality test and the socio-emotional traits hostile attribution bias and grit). Lastly, we include firm fixed effects and dummies for occupations.[20] By including cognitive and non-cognitive skills as well as firm fixed effects we can control for a large amount of otherwise unobserved worker and firm heterogeneity.

Results are displayed in Table 1. One caveat of including many controls is that we could run into a "bad controls" problem: we control for firm fixed effects and occupation, but these variables could themselves be part of an individual's choice, given his skills. If this were the case, we would be over-controlling, especially if particular firms attract particular workers and pay differential wages. We include covariates successively, and comparing results with and without firm fixed effects and occupation dummies shows that including firm fixed effects increases the size and significance of some of our covariates. This leads us to conclude that, indeed, particular firms might attract particular workers and means that column (5) of Table 1 reports our preferred estimates. This simple model is able to explain 49 percent of the variation in hourly current wages.

In accordance with literature from developing countries (e.g. Kuépié et al., 2009; Söderbom et al., 2006), we find convex returns to education; this means that returns to education increase with the level of education attained.[21] To illustrate the non-linearity of returns to education, we tested a specification with education dummies instead of a continuous education variable. Returns to education are insignificant at 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 returns are significant and increasing with the level of education obtained, with

[18] 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 assume that any significant results are caused by differences in hiring channels and not in formality status.

[19] The data allow us to split total work experience into work experience prior joining the current firm and tenure at one's current job. However, we decided against using the more disaggregated measures due to the inherent endogeneity of tenure.

[20] We include dummies for 10 different occupations: managers, professionals, technicians and associate professionals, clerical support workers, service workers, sales workers, skilled agricultural workers, construction and related workers, machine operators/drivers, and elementary occupations.

[21] We also estimated a basic model with a linear education term. We find a wage return of 6.9 percent to an additional year of education, which is in line with other studies for Bangladesh, such as Asadullah (2006), who uses national household survey data from 1999-2000 and finds returns of 6.2 percent for men. However, as our squared years of education term is highly significant, we will continue with a non-linear specification of education.

Table 1 – Log hourly wages regressed on cognitive and non-cognitive skills, OLS

Log hourly wages	(1)	(2)	(3)	(4)	(5)
Years of education	-0.007	-0.007	-0.014*	-0.024***	-0.028***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Years of education (sqrd)	0.004***	0.004***	0.004***	0.005***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OP (std)		0.001	0.003	0.004	0.001
		(0.011)	(0.009)	(0.009)	(0.009)
CO (std)		-0.011	-0.019*	-0.021*	-0.020*
		(0.012)	(0.011)	(0.012)	(0.011)
EX (std)		0.015	0.001	0.002	0.005
		(0.012)	(0.009)	(0.009)	(0.009)
AG (std)		0.003	0.013*	0.014**	0.011*
		(0.009)	(0.007)	(0.007)	(0.007)
ES (std)		0.004	0.007	0.007	0.008
		(0.013)	(0.011)	(0.011)	(0.010)
HAB (std)		0.003	-0.010	-0.010	-0.013*
		(0.009)	(0.008)	(0.008)	(0.007)
GR (std)		0.005	0.005	0.004	0.001
		(0.011)	(0.009)	(0.009)	(0.009)
Reading score				0.040***	0.034**
				(0.013)	(0.013)
Numeracy score				0.005	0.005
				(0.013)	(0.012)
Indvl controls	YES	YES	YES	YES	YES
Firm fixed effects			YES	YES	YES
Occupation dummies					YES
N	4,678	4,678	4,678	4,678	4,678
R^2	0.459	0.459	0.433	0.461	0.485

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, total work experience and total work experienced squared. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Numeracy and literacy scores are standardized.

returns highest for those who have obtained a post-graduate degree.[22] This pattern suggests low-quality primary education in Bangladesh but could also be due to a different reward structure to educational attainment in the formal sector (Kuépié et al., 2009).

Cognitive skills have a positive effect on wages, even when controlling for educational attainment. Returns are rather low, however: column (5) shows that a one standard deviation increase in the literacy score increases wages by only 3.4 percent. Estimates for developed countries range between 3.8 percent in Sweden to 20 percent in the United States (Hanushek and Zhang, 2009), but these estimates look at annual earnings and not wages; estimates for developing countries might be even larger, though results seem to depend on the estimation strategy and sample (Hanushek and Woessmann, 2008).

In terms of non-cognitive skills, we find several significant covariates: a one standard deviation increase in conscientiousness is associated with a 2 percent decreases in log hourly wages; a similar increase in hostile attribution bias is associated with a 1 percent decrease in wages. An increase in agreeableness is associated with a positive wage premium, however. These findings only appear after we include firm fixed effects in column (3), and the significant coefficient for hostile attribution bias only shows once we also include occupation dummies. This suggests that firm specific wage setting, rewarding particular skills differently (and doing so by occupation, in the case of hostile attribution bias), is driving our results. This is intuitive, as one could

[22]Table not shown but available upon request.

imagine a firm in the manufacturing sector to not care much about a workers' agreeableness if that person works in construction, while this could be particularly important for somebody working in customer care in a firm in commerce.

As a robustness check, we also constructed non-cognitive skills variables using exploratory factor analysis instead of relying on pre-defined definitions. Three factors can be identified in the data. The first is made up of mostly items from the extraversion and emotional stability scale; the second relates to work ethic (conscientiousness and grit); the third captures openness to experience and agreeableness. Building non-cognitive skills from exploratory factor analysis instead of pre-defined dimensions reduces our sample size to 3,102 observations, as not every worker completed the full non-cognitive skills questionnaire. Using these factors in the OLS regressions (shown in columns (1) to (3) of Table A.4) illustrates that none of the factors are significant in the OLS wage regressions, though the coefficients carry the same signs as in Table 1 (i.e. positive sign for factor 1 and a negative sign for factor 2). Due to the drop in sample size, we will rely on the separate Big Five dimensions for the remainder of the paper and refer to the constructs from factor analysis as robustness checks.

An additional potential caveat of including education, learning outcomes (literacy, numeracy), and non-cognitive skills is that we potentially introduce multicollinearity into our estimations. This is rather obvious for the case of education and literacy and numeracy, given that the latter are usually developed in the educational system. It is, however, also possibly the case for the non-cognitive skills variables, since they have been shown to influence schooling outcomes (educational attainment) and learning (through effort applied, for example) (e.g. Cunha and Heckman, 2008; Heckman and Rubinstein, 2001). We therefore test for multicollinearity in the OLS regressions by looking at the variance inflation factor (VIF). The VIF is the ratio of the variance of a multiple covariate model to the variance of a single covariate model. As a rule of thumb, a VIF larger than 10 is seen as a sign of multicollinearity (see e.g. Hair et al., 1998). Table A.5 displays the variance inflation factors per covariate included for different OLS specifications. According to this rule, the VIFs for education and education squared are too high in the very basic Mincer model displayed in column (1). Comparing a basic Mincer model (column (1)) to a slightly augmented one including non-cognitive skills (column (2)) shows that including additional covariates does not change the VIF of those in the basic model. Further, the VIF for the included non-cognitive skills are all rather low (ranging from 1.1 to 2.1). Including learning outcomes in column (3) substantially increases the VIF for years of schooling from 13.3 to 17.1 but leaves the non-cognitive skills unaffected. Thus, the problematic variable in terms of multicollinearity is education. Indeed, column (4) without the education variables shows that the VIF for every covariate is below 10, and the value of literacy's VIF drops. This illustrates that multicollinearity does not seem to be a problem when it comes to education and non-cognitive skills, or non-cognitive skills and learning outcomes[23], but multicollinearity is present when including both years of schooling and literacy. We thus estimate our preferred OLS regression from Tables 1 without years of education (and its square) as covariates. OLS results are displayed in column (1) of Table A.6 and show that the coefficients for the non-cognitive skills remain unchanged. The coefficient for literacy more than doubles in size, though, from 0.034 with education covariates to 0.088 without. The collinearity between education and literacy could occur for a number of reasons. For example, both literacy and years of schooling are outcomes of cognitive (intelligence) and non-cognitive skills. If this were the driving force behind the collinearity though, one would also expect numeracy to be highly collinear (which does not react to whether or not education is included) and for both literacy and education to be sensitive to

[23]Indeed, additional models, not shown, demonstrate that starting the models with cognitive skills and subsequently adding non-cognitive skills leaves the VIF of cognitive skills basically unchanged.

the inclusion of the non-cognitive skills. Since this is not the case, it seems more likely that the ability to read and write could act as a signal for the quality of education received, particularly in an environment where educational quality is diverse, which is why we decide to keep both literacy and education in our main regressions.

5.2.2 Earnings

While most of the paper is based on hourly wages, this section provides a descriptions of returns to total individual earnings. This is useful as one component of the returns to skills might be differences in labor supply. Table A.7 depicts the returns to total current earnings. Results are broadly comparable to those in Table 1, with the only difference being that hostile attribution bias is no longer significant when looking at current earnings. Indeed, looking at the determinants of hours worked (column (6)) shows that hostile attribution bias is the only significant determinant of hours worked that we can find, with those being more hostile towards others working more hours. This suggests sorting of people with high hostile attribution bias (who thus think that others around them might be hostile towards them) into jobs with a high hourly requirement, but not necessarily high pay. Indeed, those with higher hostile attribution bias can mostly be found in unskilled occupations. This supplemental analysis suggests some potential labor supply responses; for comparability reasons, we will be focusing on hourly wages for the remainder of this paper.

5.3 Choice of hiring channel

The OLS wage estimates are likely to be biased if the skills variables we are looking at (cognitive and non-cognitive) predict the hiring channel a worker chooses. Table 2 presents a probit model in which the dependent variable is the probability of having been hired through social networks. This model is the first equation of the selection model (equation 5) that will be developed in subsequent sections. We start from a basic model with only the identifying variables (mother's education and monthly household income), education, and non-cognitive skills, and subsequently add cognitive skills, occupational dummies, and firm fixed effects. Moving from a model without fixed effects (column (2)) to a model with fixed effects (column (4)) reduces our sample size, as the fixed effect model relies on at least one formal and one network-hired worker per firm for identification. This is not the case for 229 out of 487 firms in our sample and shows that not all firms use both hiring channels. The single-hiring-channel firms are mostly from education and public administration for those who only hire through the formal channel and manufacturing for those who only hire through networks. Keeping only firms that have more than one hiring channel is essential as we are interested in why firms would hire workers through one channel or the other. However, this means, on aggregate, that in our preferred specifications with firm fixed effects our sample has slightly fewer manufacturing firms compared to the original sample.

Results in Table 2 show that after including firm fixed effects, non-cognitive skills do not have any significant relation with hiring channels. Contrary to our hypothesis, being more agreeable, for example, does not significantly increase one's probability of having been hired through networks. In addition to our selection identification variables, the only significant predictors of having been hired through networks are years of schooling and the reading score. For both covariates, the effect goes in the same direction: an additional year of schooling and a better reading score both reduce the probability of having been hired through networks. On the one hand, this result could be due to individuals without literacy skills being unable to access formal means of job search (such as newspaper adds). On the other hand, literacy could act as a signal for having received a quality education. If it is difficult for employers to assess the real quality of a degree received, requiring workers (in formal job ads) to be literate could work as a proxy for quality.

Table 2 – Probability of being hired through social networks: marginal effects after probit

Hired through networks	(1)	(2)	(3)	(4)
Years of education	-0.078***	-0.050***	-0.059***	-0.040**
	(0.012)	(0.012)	(0.016)	(0.017)
Years of education (sqrd)	0.000	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
OP (std)	-0.005	-0.003	0.003	0.003
	(0.013)	(0.012)	(0.019)	(0.019)
CO (std)	0.030*	0.028*	0.007	0.010
	(0.016)	(0.016)	(0.021)	(0.022)
EX (std)	-0.005	-0.006	-0.015	-0.017
	(0.015)	(0.014)	(0.021)	(0.020)
AG (std)	0.007	0.004	0.015	0.013
	(0.011)	(0.011)	(0.015)	(0.015)
ES (std)	0.014	0.016	0.028	0.026
	(0.015)	(0.014)	(0.019)	(0.019)
HAB (std)	-0.011	-0.009	-0.013	-0.013
	(0.011)	(0.011)	(0.015)	(0.015)
GR (std)	-0.011	-0.011	-0.013	-0.011
	(0.013)	(0.012)	(0.017)	(0.018)
Reading score		-0.071***		-0.057**
		(0.019)		(0.026)
Numeracy score		0.011		0.004
		(0.017)		(0.025)
Mother no formal educ	0.127***	0.120***	0.134***	0.122***
	(0.026)	(0.025)	(0.034)	(0.034)
HH inc: 5,000-7,500tk	-0.063	-0.065	-0.161*	-0.141
	(0.066)	(0.065)	(0.092)	(0.094)
HH inc: 7,501-10,000tk	-0.072	-0.095	-0.184**	-0.163*
	(0.066)	(0.067)	(0.093)	(0.094)
HH inc: 10,001-15,000tk	-0.042	-0.080	-0.234**	-0.200**
	(0.067)	(0.068)	(0.095)	(0.096)
HH inc: 15,001-20,000tk	0.006	-0.044	-0.203**	-0.165
	(0.070)	(0.072)	(0.100)	(0.102)
HH inc: 20,001-30,000tk	-0.079	-0.175**	-0.302***	-0.275**
	(0.076)	(0.077)	(0.108)	(0.111)
HH inc: 30,001-50,000tk	0.088	-0.012	-0.205	-0.182
	(0.092)	(0.098)	(0.127)	(0.131)
HH inc: 50,001tk and above	0.091	-0.024	-0.085	-0.070
	(0.164)	(0.170)	(0.229)	(0.237)
Indvl controls	YES	YES	YES	YES
Occupation dummies	YES	YES	YES	YES
Firm fixed effects			YES	YES
N	4,655	4,655	3,110	3,110
Pseudo R^2	0.287	0.328	0.357	0.361

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, work experience and work experienced squared. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Literacy and numeracy scores are standardized. Marginal effects reported are at the means of covariates. Our sample size is reduced to 4,655 individuals instead of 4,678 due to missing values in the household income variable.

So far, we have combined all types of social networks into one category. However, the type of social network activated might matter for wages. We can distinguish between one formal hiring channel and four different types of social networks (family, friends, village connections, and political and school alumni associations). The number of observations within each channel is balanced, except for the last category.[24] Due to the small number of observations in the politics and school category and based on the suggestions of a Wald test for combining categories, we will combine it with the friends category. Table A.8 depicts the result and demonstrates the relevance of both of our identifying variables. Crucially, the estimates are based on firm characteristics (industry, size, whether the firm exports, and gender of the CEO) instead of firm fixed effects, as models with the latter would not converge. As we are therefore not able to fully control for firm heterogeneity in the hiring decision, the results presented in this section should be handled with caution.

Results are similar compared to the binary distinction between formal hiring channels and networks only in the sense that we find that the literacy score increases a worker's probability of having been hired through formal channels and decreases his probability of having been hired through family or through friends. It is insignificant for the village hiring channel. Looking at the non-cognitive skills now also reveals significant results, though, they differ by channel: emotional stability is positive and significant among those hired through family connections, as is grit, but the latter decreases one's chances of being hired through friends. Further, hostile attribution bias is negatively related to being hired through village connections. This suggests that there could be a role for non-cognitive skills in affected hiring channels; still, given that we only control for firm characteristics and not firm fixed effects, we place less emphasis on this result.

5.4 Skills and endogenous hiring channel

The results from the previous section illustrate that cognitive skills influence the selection of hiring channel, while less evidence is found for non-cognitive skills, as when we distinguish between the different Big Five traits, none of them is statistically significant. Still, to account for the selection into hiring channel based on literacy skills, the following section presents the switching model. Table 3 depicts the results, modeling selection as a bimodal choice between formal channels and networks. Columns (1) and (2) of Table 3 depict the wage regression for the formal hiring channel, equation (2), and columns (4) and (5) the wage regression for the network hiring channel, equation (3), both while first taking into account selection into hiring channel. Columns (3) and (6) present OLS estimations for comparison.

Results show that selection is indeed present; both inverse mills ratios (IMR) are significant. The IMR for the formal hiring channel is negative, meaning that without the selection correction, the estimates would have been biased downwards. Returns estimated from the OLS are thus likely to be lower than the true returns once we take selection into account. The opposite holds true for the IMR for the network hiring channel. Looking at selection corrected estimates, we find that 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 negative – but effectively equal to zero in the network channel. Literacy skills, which were highly significant in the OLS regressions and in the selection equation, do not show any significant association with wages 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 thereby act only by enabling workers to access the formal hiring channel; once a worker has been hired through the formal channel, the role of literacy vanishes. Thus, the positive literacy coefficient in the OLS regressions (Table 1) simply captures a wage premium for having been hired through formal channels.

Non-cognitive skills, none of which were significant in the selection equation when looking

[24] 960 workers found their job through family members, 1,012 through friends, and 489 through village connections, but only 76 workers found their job through political and school alumni associations.

Table 3 – Returns to skills using an endogenous switching model

Log hourly wages	Formal hiring			Network hiring		
	Selec Corr (1)	Selec Corr (2)	OLS (3)	Selec Corr (4)	Selec Corr (5)	OLS (6)
Years of education	-0.041***	-0.051***	-0.028	-0.021***	-0.028***	-0.030***
	(0.015)	(0.016)	(0.019)	(0.005)	(0.006)	(0.009)
Years of education (sqrd)	0.005***	0.003***	0.003***	0.004***	0.003***	0.004***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
OP (std)	0.027**	0.025**	0.024*	-0.010	-0.013	-0.013
	(0.011)	(0.010)	(0.013)	(0.009)	(0.008)	(0.012)
CO (std)	-0.025*	-0.023*	-0.028	-0.017	-0.017	-0.019
	(0.014)	(0.014)	(0.018)	(0.011)	(0.011)	(0.015)
EX (std)	0.005	0.008	0.013	0.003	0.001	0.003
	(0.014)	(0.013)	(0.015)	(0.010)	(0.010)	(0.012)
AG (std)	0.017	0.011	0.009	0.012	0.011	0.010
	(0.011)	(0.010)	(0.011)	(0.008)	(0.008)	(0.010)
ES (std)	0.002	0.004	0.000	0.017	0.019*	0.017
	(0.014)	(0.013)	(0.016)	(0.011)	(0.010)	(0.013)
HAB (std)	-0.022**	-0.023**	-0.020	-0.009	-0.013*	-0.012
	(0.010)	(0.010)	(0.013)	(0.007)	(0.007)	(0.010)
GR (std)	-0.005	-0.011	-0.007	0.006	0.003	0.003
	(0.011)	(0.011)	(0.015)	(0.009)	(0.008)	(0.011)
Reading score		0.026	0.049*		-0.005	0.001
		(0.019)	(0.026)		(0.012)	(0.015)
Numeracy score		0.001	-0.004		0.012	0.012
		(0.015)	(0.024)		(0.009)	(0.014)
Indvl controls	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES
Occupation dummies		YES	YES		YES	YES
Inverse Mills ratio	-0.267***	-0.250***		0.114**	0.150***	
	(0.055)	(0.052)		(0.049)	(0.048)	
N	4,655	4,655	2,127	4,655	4,655	2,528
R^2			0.687			0.672

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, work experience and work experienced squared. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Instruments used for identification: mother has no formal education and monthly household income. Estimated using a two-step model. Our sample size is reduced to 4,655 individuals instead of 4,678 due to missing values in the household income variable.

at binary selection (formal vs. networks), are significant in the wage regressions. For those hired through formal channels as well as those hired through networks, hostile attribution bias decreases wages. Hostile attribution bias refers to a cognitive bias according to which individuals interpret others' action towards them as hostile. In a work setting, such an individual is likely to be less effective in any setting that involves other workers, such as teamwork or communication with customers or suppliers. A negative effect of hostile attribution bias is thus expected (except for maybe management positions, where adverse behavior and a suspicion towards others could feasibly lead to more success). The negative effect of conscientiousness on wages that we found in the combined OLS regressions in Table 1 is in fact driven by those in the formal hiring channel. As mentioned previously, hiring channel does coincide with occupational selection. As such, those hired through formal channels are more likely to work in white-collar occupations, in which conscientiousness and a high level of attention to detail (doing work very thoroughly) might not be strictly required. Instead, traits that could be more important might be those related to creativity and coming up with new ideas. Indeed, the trait correlating with that sort of behavior, openness to experience, is highly significant for those hired through formal channels (and even shows up in the formal-channel only OLS regression in column 3). Looking at those hired through networks, emotional stability is the only trait that exhibits a positive and significant correlation with wages. While the trait is only significant at the 10 percent level, it could relate to workers being better able to remain balanced throughout the work day, to be tolerant of others' behaviors, to perform tasks well, and to not be stressed easily. This then also captures dimensions of agreeableness, which is no longer significant in either hiring channel.

Columns (3) and (6) provide results from separate OLS regressions by hiring channel for direct comparison with the selection-corrected returns. For formal channels, the coefficients for most non-cognitive skills are similar in size but increase in significance when taking into account selection. This is in line with expectations, given the negative IMR. The coefficient for years of education almost doubles in size and becomes highly statistically significant when taking into account selection, while the coefficient for reading score is halved and loses its significance. For network hiring, a similar effect is not visible and coefficients for the selection-corrected estimations in column (5) and basic OLS in column (6) are very similar in terms of coefficient size. The selection corrected standard errors are slightly smaller, meaning that some of the coefficients gain significance. Still, it seems that selection into formal channel is more prevalent than selection into network hiring. This suggests that network hiring could be a secondary option when looking for work, or that it is the only option available for some low-skilled workers. In sum, the returns to different personality traits seem to mirror the types of tasks that individuals hired through each channel perform, which are more likely (though not exclusively so) higher skilled, more white-collar occupations for those hired through formal channels, and low- or unskilled (possibly manual or menial tasks) for those hired through networks.

The different rewards to skills by hiring channel give rise to the notion that firms might hire workers through different channels depending on their occupation (i.e. blue-collar workers being hired predominantly through social networks, with white-collar workers hired largely through formal channels). The data do not fully discount this claim: about 40 percent of workers in the sample work in blue-collar jobs and 78 percent of them were hired through networks (compared to only 39 percent of workers in white-collar occupations). We illustrate differential returns by broad type of occupation (blue- and white-collar), by introducing interactions between non-cognitive skills and being a white collar worker (Table A.9).

For network hires, all interaction terms except for grit are insignificant. Being gritty and a white-collar worker actually has a surprising negative return for those hired through networks. This is unexpected and does not only affect a small number of people, as about 40 percent of those hired through networks are white-collar workers. It could suggest that what is wanted from those workers is creativity (relating back to the positive effect of openness in formal channels in Table 3, which is also positive here, but insignificant), or that other traits such as obedience and listening to one's superiors are more important than persistence and task completion. Among formal channels, being a white-collar worker is only significantly associated with emotional stability. Conscientiousness is still negative but no longer significant. Table A.9 thus suggests that there might be differential returns depending on broad occupational type, though the evidence is not particularly conclusive. One has to keep in mind that among those hired through formal channels, only about 20 percent of the sample are not in white-collar jobs and are thus a potentially non-representative comparison group.

In addition to the bimodal selection model, we estimate multinomial models with four different states: one formal hiring channel and three informal hiring channels (family, friends, and village connections). Table A.10 depicts wage returns to skills, taking into account this multinomial selection. Few of the ρ, the selection coefficients, are significant, which means that our model attempts to correct for selection which might not even be present. This could be driven by us being unable to fully account for firm heterogeneity in hiring decisions, as we only include firm characteristics. Given that, and a different selection correction using Bourguignon et al. (2007), results in Table A.10 are not necessarily comparable to those obtained earlier. Differences in returns to skills by more disaggregated hiring channel, distinguishing between the different networks used, are visible, but only one trait (emotional stability) is significant in only one channel (friends). These results show that there could be differences depending on which network was activated to find the job, but, they are at best suggestive and certainly not conclusive.

5.5 Starting wages and wage growth

In addition to looking at current wages, our data allow for an analysis of starting wages and thus also wage growth (the difference between current and starting wages). This is especially interesting when it comes to wage returns to skills, as employers cannot fully observe a worker's skillset 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 to predict productivity and set starting wages accordingly. Over time, wages are then adjusted to match observed productivity. Similarly, the different hiring channels offer different opportunities for employers to obtain information about a potential employee prior to hiring – either through information obtained in the formal hiring process (such as personal interviews or assessment centers) or by means of information received through networks (such as who recommended the applicant or a personal assessment of the applicant by the recommending person). All of our variables are measured at the same point in time, the present. However, some of them can be assumed to be constant over time and thus be important for wage setting. This holds especially true for levels of formal education (assuming that most workers do not engage in further formal education once they are employed and would only benefit from on-the-job-training), but it also most likely holds for non-cognitive skills. Indeed, non-cognitive skills are assumed to be rather stable throughout adult life and have been shown to only react slightly to major life events (Cobb-Clark and Tan, 2011). As the mean age at hiring in our sample is 26 years, we assume that while the survey (and its skills assessment) was conducted after the worker had started his current job, skills have not changed significantly between hiring and the time of assessment. For literacy and numeracy skills, the assumption seems to be a little more dubious: somebody who uses these skills a lot as part of his workday might improve on these measures, while somebody who does not use them might lose proficiency.

Table 4 presents the switching model for starting wages and wage growth, as well as separate OLS regressions for comparison. We identify the selection equation only via the educational attainment of the mother, as household income is only available at present time and could have been different when workers began their jobs.

Looking at the starting wages regressions reveals similar results as present wages: openness to experience has a positive and significant return for those hired through formal channels, conscientiousness is once again negative, and agreeableness is positive (and significant this time). Hostile attribution bias is no longer significant, though it remains negative. All of these are traits that can arguably be identified during a formal interview; the employer could observe if the worker is open to new ideas and thinks outside the box (openness to experience), if he is organized or not (conscientiousness), and whether or not he is friendly (agreeableness). Hostile attribution bias might not show during an interview (or the worker might attempt to hide it), which likely is why it is not punished at initial wage setting. However, once a worker is observed on the job, this trait could more readily show and therefore influence future wage development. It thus seems that employers do reward individuals for traits they deem desirable and can observe

Table 4 – Returns to skills using an endogenous switching model - Starting and current wage

	Starting wage				Wage growth			
	Formal		Network		Formal		Network	
	OLS	SelCor	OLS	SelCor	OLS	SelCor	OLS	SelCor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Years of education	-0.014	-0.027	-0.020	-0.019**	0.008	0.011*	0.001	0.001
	(0.028)	(0.024)	(0.012)	(0.008)	(0.008)	(0.005)	(0.002)	(0.001)
Years of education (sqrd)	0.003**	0.003***	0.004***	0.003***	-0.000	-0.000*	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Reading score	0.007	-0.004	0.014	0.013	-0.002	-0.001	0.002	0.003
	(0.031)	(0.028)	(0.024)	(0.016)	(0.006)	(0.006)	(0.004)	(0.003)
Numeracy score	0.010	0.012	0.012	0.011	-0.006	-0.007	-0.001	-0.001
	(0.030)	(0.023)	(0.018)	(0.013)	(0.005)	(0.005)	(0.003)	(0.002)
OP (std)	0.024	0.025*	-0.022*	-0.021*	0.006	0.005	0.002	0.001
	(0.019)	(0.015)	(0.013)	(0.011)	(0.004)	(0.003)	(0.002)	(0.002)
CO (std)	-0.040*	-0.039*	-0.032	-0.031**	-0.009*	-0.009*	0.005	0.005*
	(0.024)	(0.020)	(0.021)	(0.015)	(0.005)	(0.004)	(0.003)	(0.003)
EX (std)	-0.001	-0.001	0.016	0.015	-0.005	-0.005	-0.004	-0.004
	(0.028)	(0.019)	(0.016)	(0.013)	(0.006)	(0.004)	(0.003)	(0.002)
AG (std)	0.025	0.028*	0.012	0.013	-0.002	-0.002	-0.001	-0.001
	(0.019)	(0.015)	(0.014)	(0.011)	(0.006)	(0.003)	(0.002)	(0.002)
ES (std)	0.026	0.024	0.027	0.030**	0.005	0.005	-0.002	-0.002
	(0.029)	(0.020)	(0.018)	(0.014)	(0.004)	(0.004)	(0.003)	(0.002)
HAB (std)	-0.010	-0.012	-0.008	-0.011	-0.003	-0.002	0.000	0.001
	(0.019)	(0.014)	(0.011)	(0.010)	(0.003)	(0.003)	(0.002)	(0.002)
GR (std)	0.019	0.015	-0.006	-0.007	-0.001	-0.001	0.004*	0.004*
	(0.020)	(0.016)	(0.016)	(0.012)	(0.004)	(0.004)	(0.002)	(0.002)
Occup dummies	YES	YES	YES	YES	YES	YES	YES	YES
Firm fixed effects	YES	YES	YES	YES	YES	YES	YES	YES
Indvl controls	YES	YES	YES	YES	YES	YES	YES	YES
Inverse Mills ratio		-0.113		0.055		0.020		-0.014
		(0.083)		(0.068)		(0.019)		(0.012)
N	2,127	4,678	2,528	4,678	2,127	4,678	2,528	4,678
R^2	0.541		0.550		0.205		0.313	

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, prior work experience, prior work experienced squared, and age at entering the firm. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Numeracy and literacy scores are standardized. Instrument used for identification: mother has no formal education. Estimated using a two-step model, showing the second stage of that model. SelCor stands for selection corrected estimates.

during worker selection.

Among network hires, openness to experience, and conscientiousness are punished during initial wage setting and emotional stability is rewarded. When workers are hired through networks, the only information that the employer has is through information they can gather from the network. Employers could hire through networks because it allows them to select unobservably good workers, as networks might have information that employers could not observe. They could also hire through networks because it allows them to mitigate a moral hazard problem, punishing referral providers if the referred worker does not perform well. Heath (2018) finds evidence of the latter mechanism at play in Bangladeshi garment factories. Our data do not allow us to distinguish between both mechanisms (in fact, we do not even know if the job was obtained as a referral, or if networks simply provided information about a job opening). Still, given a comparable setting, if the moral hazard mechanism was at play, workers that would be referred could arguably be those who are more emotionally stable – and therefore less likely to suffer from stress and anxiety and to be more productive as a result (Drago, 2011). This could also explain why workers do not seem to benefit from higher openness to experience, which refers to workers who are curious and prefer new experiences to routines.

Taking wage growth instead of current wages or starting wages as the dependent variable reveals a small but significantly positive effects of grit and conscientiousness for hired through networks and a small but significantly negative effect for those hired through formal channels. Among the latter group, this again reflects that employers probably value creativity and coming up with new ideas more than simply executing tasks on time. In the wage growth equations, individual effects that are constant over time should have zero effect on wage growth, due to differentiation between current and starting wage equations which they enter in similar ways. As we observe a positive and significant effect of conscientiousness and grit among network hires, one possible explanation is that these traits evolve over time as workers improve their performance and adapt closer to work requirements. Lastly, the inverse mills ratios are insignificant for both, the network and the formal hiring channel (though with the same sign), meaning that estimates from OLS and after correcting for selection are very similar. This could be driven in part by our ability to include only one instrument to identify selection instead of two and thus our consequent inability to fully account for a worker's decision to engage in formal or network job search. At the same time, starting wages could also simply be measured with more error, as workers do not remember them accurately.

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

Finally, we aim 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 – about two thirds of the sample used in previous sections. Table A.11 presents characteristics of the firms included in this restricted sample in comparison to the sample of firms used in previous sections. Compared to the switching model section, our firms in this section are slightly more likely to be in commerce and manufacturing and less likely to be in public administration. Firms in the reduced sample are, on average, bigger than firms in the original sample, which is to be expected when we impose the restriction of having at least two formal and two network hires per firm. 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 returns to skills are affected 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 et al., 2015; Nordman and Wolff, 2009) 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.

As before, we include firm fixed effects in our worker-level wage equations for formal and network hires and estimate those as follows:

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

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

In the regression analysis, we control for a worker's demographic characteristics, A, his cognitive skills Cog and non-cognitive skills $NonCog$. Due to these controls, the effect of the firm fixed effect, δ, then simply reflects a premium paid by the firm to its employees beyond their observable characteristics. The difference between δ_j^F and δ_j^N can thus 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.

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

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 sex 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 and the importance of a number of skills in the hiring decision among two types of workers in their firm, namely professional workers (managers, professionals, technicians) and non-professionals (such as clerical support workers, construction, and elementary occupations). The employers were thus asked not to judge an individual employee but a broad group of occupations. Employers were asked (on a scale of 1-10) how important they think it is for their employees to have the following skills: communication, teamwork, problem solving, literacy, numeracy, costumer care, responsibility, motivation, and 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. Standardized values of these skills variables are included in the regression (vectors $SkillsEmployees_j$ and $SkillsHiring_j$, respectively). As the questions were asked separately for both broad occupational types, we also run separate regressions and, in line with the distinction between white- and blue-collar workers earlier in this paper, do not expect to obtain the same results for each professional group.

We normalize the within-firm wage gap to be 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 0.11, as the distribution is quite skewed. We drop the five most unequal firms, which leaves us with a sample mean of 0.48. Figure A.2 shows that the within-firm wage gap is approximately normally distributed (panel a) and that it is not concentrated in a single industry (panel b).

Table 5 displays the results of equation 8, separately for professional and non-professional workers. A positive coefficient refers to an increased within-firm wage gap between formal and network hires (i.e. formal hires enjoying a wage premium beyond their observable characteristics); a negative coefficient symbolizes the opposite. Looking at the regression for professional workers, an employer placing more value on communication skills, correlates with a larger wage gap between formal and network hires. An employer placing more value on teamwork skills, is associated with a smaller wage gap, meaning that workers hired through formal channels and networks earn wages that are comparatively equal. No significant correlation is visible for non-professional workers in column (2).

From a theoretical point of view, employers could choose to hire through networks instead of formal channels for two main reasons: networks could provide information about potential workers that would otherwise be unobservable, and hiring based on referrals could reduce moral hazard, as referees can be punished as well if referred workers do not perform according to

Table 5 – Determinants of the within-firm hiring channel wage gap

Normalized within-firm wage gap	Professional worker (1)	Non-professional worker (2)
Importance of skills among employees		
Communication skills	0.032*	-0.003
	(0.018)	(0.020)
Team work skills	-0.052***	0.002
	(0.020)	(0.024)
Problem solving skills	0.008	-0.034
	(0.021)	(0.023)
Literacy skills	-0.007	-0.000
	(0.022)	(0.019)
Numeracy skills	0.009	0.005
	(0.021)	(0.018)
Customer care skills	-0.007	-0.016
	(0.017)	(0.018)
Responsibility	-0.023	-0.018
	(0.020)	(0.026)
Motivation	0.006	0.026
	(0.022)	(0.028)
Creativity	0.007	0.025
	(0.025)	(0.023)
Vocational job-specific skills	-0.012	-0.034
	(0.019)	(0.023)
Importance in hiring decision		
Academic performance	0.008	0.001
	(0.018)	(0.016)
Work experience	0.024	0.019
	(0.016)	(0.019)
Skill set	-0.008	0.017
	(0.019)	(0.020)
Interview	-0.004	-0.002
	(0.021)	(0.020)
Network/Recommendation	-0.019	-0.013
	(0.016)	(0.014)
Political affiliation	0.022	0.033
	(0.018)	(0.059)
Firm characteristics	YES	YES
N	171	171
R^2	0.239	0.240

Notes: Standard errors are bootstrapped (500reps); *** p<0.01, ** p<0.05, * p<0.1. Firm characteristics include industry, firm size, a dummy for exporting firms, whether the firm has performance reviews, whether it has bonuses based on firm performance, or individual performance, whether it requires interviews for vacancies, a dummy for the main job advertising channel being networks, whether the firm provides on the job training, the proportion of the top management being women, the gender of the manager answering the questionnaire and their educational attainment.

expectations. Heath (2018) has shown that the latter mechanism is at play among Bangladeshi garment workers, and section 5.5 has demonstrated that a similar mechanism could be at play here, since hiring channels do correlate with occupational attainment, with those being hired through networks more likely to work in lower skilled occupations, more similar to those observed in Heath (2018). Table 5 illustrates, that in fact, both explanations could be valuable in the data set at hand. The category 'professional workers', displayed in column (1), captures very high-skilled workers, from managers to technicians and associates. Among those, a significant share is still hired through networks (about 38 percent). Among these highly skilled workers, moral hazard is arguably less of a problem as they might be more motivated; instead, the employer could use networks to capture otherwise unobservable characteristics. Applying this to Table 5, employers might reasonably observe a potential employees' communication skill during a formal job interview. If communication skills are important to the employer (or specific position), the employer would then predominantly search through formal channels. Indeed, if the employer thinks communication skills among their professional workers is important, the within-firm wage gap between formal and network hires is larger. Teamwork, on the other hand, might be more difficult to observe in a job interview (unless the employer is willing to include a group exercise). If the employer thinks that teamwork is an essential skill, they might predominantly search through social networks, which could provide information about how a potential worker would engage in a teamwork setting. Actually, if the employer deems teamwork important, the within-firm wage gap between formal and network hires decreases. This suggests that employers could be strategic in terms of which hiring channel to use, depending on what type of skills they require and the ability of the hiring channel to provide information about this skill.

We do not observe any significant correlation between skill importance as judged by the employer and the within-firm wage gap between formal and network hires for non-professional workers. This could be due to the fact that the skills required for non-professional workers were not part of the battery of skills included in the questionnaire (such as, for example, working diligently, not shirking, or handling stress well). If the main reason for hiring non-professional workers through social networks is to circumvent moral hazard, under the assumption that these types of occupations might not be as dependent on individual skills to ascertain a certain productivity, had we been able to, for example, observe the importance that an employer places on a worker not shirking in the questionnaire, we would have expected a negative coefficient (i.e. a smaller within-firm wage gap between formal and network hires).

6 Conclusion

This paper provides a descriptive illustration of estimates of the wage returns to educational attainment, cognitive skills (or rather learning outcomes), and non-cognitive skills while taking into account selection into hiring channel using a novel matched employer-employee data set from Bangladesh.

We aim to take into account both the potential direct and indirect effects of cognitive and non-cognitive skills on wages, focusing on one indirect effect – the choice of hiring channel. The interplay between skills and hiring channel in determining labor market outcomes is a particularly important issue in developing countries, where the role of social networks is large and research on the effects of non-cognitive skills scarce. We incorporate the fact that the same unobserved characteristics could drive both the selection of the hiring channel and the wage through endogenous switching models. The data further allow for an innovative exploration of both demand and supply side factors in explaining returns to skills and selection into hiring channels.

We find that a higher score on the literacy test increases the probability of choosing formal hiring channels and decreases the probability of having found a job through social networks. Non-cognitive skills do not seem to correlate with hiring channel in the bimodal model. A brief multinomial model which further distinguishes between different network based hiring channels shows a potential, but weak, role for non-cognitive skills.

Cognitive skills (literacy) affect wages only through increasing the probability of choosing the formal over other hiring channels. Once this initial selection into hiring channel has been corrected for, there are no further significant wage returns to literacy. However, it seems that in our case literacy could simply act as a signal for good quality education. Literacy and years of education are highly collinear, while this is not the case for education and non-cognitive skills. Looking at wage returns to non-cognitive skills, we see that these differ by hiring channel, which relates to different jobs being predominantly filled through one channel or the other. These significant correlations are not visible in simple OLS regressions, illustrating the benefit of first taking into account selection into different hiring channels. Those hired through formal channels benefit from higher returns to openness to experience but lower returns to conscientiousness and hostile attribution bias. Those hired through networks enjoy higher wages for higher levels of emotional stability, which has been linked to task performance, but are also punished for higher hostile attribution bias. Exploring the time dimensions of wages, we investigate whether non-cognitive skills could also contribute to wage growth. We find that for those hired through networks, grit and conscientiousness are both associated with higher wage growth over time. We should not expect any effects of individual effects that are constant over time on wage growth. The positive correlations of grit and conscientiousness with wage growth among network hires thus seem to suggest that these traits evolve over time as workers improve their performance and adapt closer to work requirements.

We then explore the demand side to understand whether firm characteristics and preferences for certain skills can help explain differential returns to skills. We find that employers who value communication skills more are associated with a larger within-firm wage gap between formal and network hires, while those who value teamwork more are associated with a smaller wage gap. These results only hold for professional workers, such as managers or technicians. We explain this by a firm's decision to hire through different channels among highly skilled workers. If an employer values communication skills, it will choose a hiring channel that allows them to observe these skills, even if this channel is potentially more costly for the employer. As communication skills are observable during formal interviews, this increases the wage gap between formal and informal hiring. Teamwork skills, on the other hand, might be more difficult to observe reliably in a simple job interview, which is why firms valuing these skills might rely more on networks to provide otherwise unobservable information about a worker. This mechanism only seems to hold for professional workers, though; among non-professional workers, other mechanisms, such as firms hiring through networks to overcome moral hazard problems such as workers' shirking as observed in Heath (2018), could dominate.

This paper illustrates that literacy remains important in developing countries by enabling workers to access their full potential – in this case by being hired through formal channels – even though it might not have an additional wage return apart from facilitating this first selection. It could also act as a signal for the quality of education received in a country where the average quality is low, with the literacy test capturing primary school-level reading skills. Despite the low level of knowledge tested, the average score even among those with a high school degree was only 6 correct answers out of 8 questions. Returns to non-cognitive skills are comparable to those found in developed countries, though our sample is also based on the formal sector only.

This paper provides a descriptive analysis of hiring channels and non-cognitive skills in developing countries and illustrates some channels that could be at work to explain why firms would choose to hire through one channel or another. To our knowledge, it is the first paper to do so in a developing country context, in which hiring through networks is highly prevalent. Future research attempting to provide more causal estimates for these mechanisms would certainly be beneficial. Our estimates show that non-cognitive skills play a potentially important role in developing countries' labor markets, but more research is necessary to understand whether and to what extent returns to non-cognitive skills differ in other labor market segments, such as in informal firms, among the self-employed, or more broadly in rural areas.

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Appendix: Tables and Figures

Table A.1 – Correlations between the skills measures

	(1) Educ	(2) Lit	(3) Num	(4) OP	(5) CO	(6) EX	(7) AG	(8) ES	(9) HAB	(10) GR
Years of education	1.00									
Literacy score	0.75*	1.00								
Numeracy score	0.49*	0.60*	1.00							
Openness to Experience	0.01	0.01	0.00	1.00						
Conscientiousness	0.01	0.00	0.08*	0.39*	1.00					
Extraversion	-0.06*	-0.09*	-0.12*	0.27*	0.48*	1.00				
Agreeableness	0.00	-0.01	0.04*	0.32*	0.40*	0.28*	1.00			
Emotional Stability	-0.04	-0.05*	-0.01	0.30*	0.65*	0.53*	0.32*	1.00		
Hostile Attribution Bias	-0.05*	-0.06*	-0.03	0.18*	0.11*	0.23*	0.23*	0.05*	1.00	
Grit	0.09*	0.12*	0.16*	-0.06*	-0.13*	-0.26*	-0.04*	-0.32*	-0.07*	1.00

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS).
Notes: The value in each cell is the pairwise correlation; *** = $p < 0.01$; Male workers only. N = 4,678.

Table A.2 – Characteristics of firms in samples

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)
N	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 A.3 – Characteristics of employees

	Mean (1)	SD (2)	Formal (3)	SD (4)	Networks (5)	SD (6)	Difference (7)	P-value Diff (8)
Age	31.68	8.38	33.30	8.10	30.31	8.37	3.00	0.00
Married	0.77	0.42	0.83	0.37	0.72	0.45	0.11	0.00
Lives in Dhaka	0.59	0.49	0.51	0.50	0.65	0.48	-0.14	0.00
Age at hiring	26.04	6.47	26.88	5.86	25.33	6.86	1.55	0.00
Work experience	6.28	6.13	6.96	6.63	5.71	5.61	1.25	0.00
Primary education	0.31	0.46	0.07	0.26	0.50	0.50	-0.43	0.00
Secondary education	0.46	0.50	0.49	0.50	0.43	0.50	0.06	0.00
Tertiary education	0.23	0.42	0.44	0.50	0.06	0.24	0.37	0.00
Literacy score	4.62	2.60	5.99	2.02	3.45	2.47	2.54	0.00
Numeracy score	5.71	2.01	6.36	1.66	5.16	2.11	1.20	0.00
Openness to experience	2.13	0.60	2.13	0.61	2.14	0.60	-0.01	0.62
Conscientiousness	2.44	0.80	2.39	0.82	2.48	0.78	-0.09	0.00
Extraversion	1.88	0.72	1.82	0.75	1.92	0.69	-0.10	0.00
Agreeableness	2.08	0.60	2.06	0.59	2.09	0.61	-0.03	0.10
Emotional stability	2.32	0.82	2.26	0.85	2.37	0.79	-0.12	0.00
Hostile attribution bias	1.86	0.73	1.84	0.71	1.87	0.74	-0.03	0.19
Grit	2.10	0.55	2.11	0.56	2.10	0.54	0.01	0.62
Log Hourly Wage	3.62	0.61	3.89	0.59	3.39	0.51	0.50	0.00
Manager	0.05	0.22	0.05	0.22	0.06	0.23	-0.01	0.27
Skilled white collar	0.55	0.50	0.76	0.43	0.38	0.48	0.38	0.00
Skilled blue collar	0.27	0.44	0.10	0.30	0.41	0.49	-0.31	0.00
Unskilled	0.13	0.34	0.09	0.29	0.16	0.37	-0.07	0.00
Permanent contract	0.91	0.29	0.96	0.19	0.86	0.35	0.10	0.00
Fixed-term contract	0.05	0.23	0.01	0.11	0.09	0.29	-0.08	0.00
Part time contract	0.03	0.16	0.02	0.15	0.03	0.17	0.00	0.35
Seasonal contract	0.01	0.10	0.00	0.00	0.02	0.14	-0.02	0.00
Found job through network	0.54	0.50	0.00	0.00	1.00	0.00	-1.00	
N	4,678		2,141		2,537			
N contract type	4,650		2,140		2,510			

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS).
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 4.

Figure A.1 – Current wages by hiring channel and industry

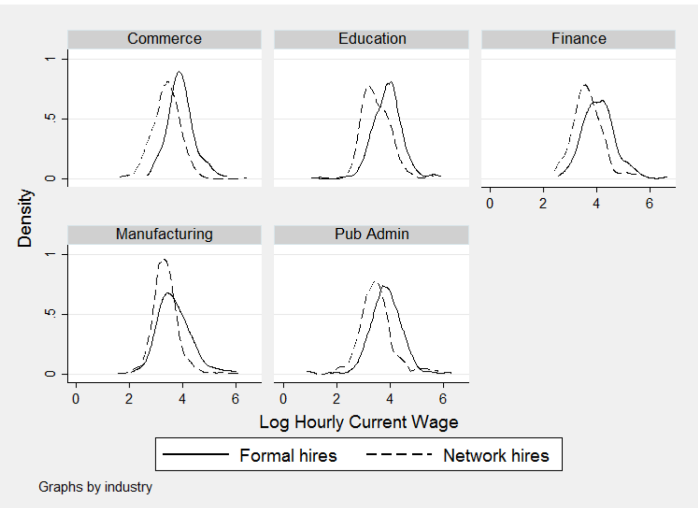

Table A.4 – Estimates for log hourly wages regressed on cognitive and non-cognitive skills with non-cognitive skills derived from exploratory factor analysis

Model	OLS:			probit:	selection correction:	
Dependent variable	log hourly wages			network hiring	log hourly wages	
					Formal	Network
	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	-0.002	-0.004	-0.022**	-0.051**	-0.044**	-0.018**
	(0.009)	(0.010)	(0.010)	(0.023)	(0.020)	(0.007)
Years of education (sqrd)	0.004***	0.004***	0.003***	0.000	0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Factor 1 (ES/EX) (std)	0.010	0.019	0.025	-0.042	-0.015	0.057***
	(0.022)	(0.019)	(0.017)	(0.044)	(0.023)	(0.018)
Factor 2 (CO/Grit) (std)	-0.008	-0.013	-0.018	0.074**	0.028	-0.038***
	(0.018)	(0.016)	(0.015)	(0.034)	(0.021)	(0.015)
Factor 3 (OP/AG) (std)	0.011	0.003	-0.003	0.016	0.010	-0.020*
	(0.012)	(0.010)	(0.009)	(0.024)	(0.013)	(0.010)
Reading score			0.035**	-0.116***	0.024	-0.007
			(0.016)	(0.039)	(0.024)	(0.015)
Numeracy score			0.006	0.010	0.008	0.001
			(0.016)	(0.033)		
Mother no formal educ				0.130***		
				(0.045)		
HH inc: 5,000-7,500tk				-0.119		
				(0.124)		
HH inc: 7,501-10,000tk				-0.138		
				(0.126)		
HH inc: 10,001-15,000tk				-0.239*		
				(0.132)		
HH inc: 15,001-20,000tk				-0.185		
				(0.141)		
HH inc: 20,001-30,000tk				-0.323**		
				(0.147)		
HH inc: 30,001-50,000tk				-0.211		
Indvl controls	YES	YES	YES	YES	YES	YES
Firm fixed effects		YES	YES	YES	YES	YES
Occup dummies			YES	YES	YES	YES
Inverse mills					-0.198***	0.144***
					(0.054)	(0.048)
N	3,102	3,102	3,102	1,974	3,096	3,096
R^2	0.459	0.412	0.474	0.396		

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, total work experience and total work experienced squared. The decrease in the sample size compared to the regressions using the Big Five is due to some non-cognitive skills variables having missing values, dropping those individuals from the factor analysis. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; GR = grit; Exploratory factor analysis based on acquiescence corrected items.

Table A.5 – Variance inflation factor for different OLS models

	Model 1 (1)	Model 2 (2)	Model 3 (3)	Model 4 (4)
Years of schooling	13.3	13.3	17.1	
Years of schooling (sqrd)	13.4	13.5	14.2	
Experience	6.2	6.3	6.3	6.2
Experience (squared)	6.0	6.0	6.0	6.0
Married	1.1	1.1	1.1	1.1
OP (std)		1.3	1.3	1.3
CO (std)		2.0	2.1	2.1
EX (std)		1.6	1.6	1.6
AG (std)		1.3	1.3	1.3
ES (std)		2.1	2.1	2.1
HAB (std)		1.1	1.1	1.1
GR (std)		1.2	1.2	1.2
Reading score			2.8	1.6
Numeracy score			1.7	1.7

Notes: Standard errors clustered at the firm-level in parentheses; OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Variance inflation factor calculated after OLS regressions. All covariates included are shown in the table. Literacy and numeracy scores are standardized.

Table A.6 – OLS and endogenous switching models without education as a covariate

Model	OLS: (1)	selection correction: Formal (2)	Networks (3)
Reading score	0.088***	0.025	0.003
	(0.013)	(0.021)	(0.015)
Numeracy score	0.003	0.000	0.015
	(0.013)	(0.016)	(0.012)
OP (std)	0.004	0.024**	-0.007
	(0.009)	(0.011)	(0.011)
CO (std)	-0.022*	-0.014	-0.021
	(0.012)	(0.015)	(0.014)
EX (std)	0.002	0.001	-0.004
	(0.010)	(0.014)	(0.013)
AG (std)	0.014*	0.010	0.017*
	(0.008)	(0.011)	(0.010)
ES (std)	0.007	0.009	0.024*
	(0.010)	(0.015)	(0.014)
HAB (std)	-0.013*	-0.028***	-0.016*
	(0.008)	(0.010)	(0.009)
GR (std)	0.008	-0.010	0.008
	(0.009)	(0.012)	(0.011)
Inverse mills ratio		-0.409***	0.420***
		(0.054)	(0.053)
N	4,678	4,655	4,655
R^2	0.434		

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. All specifications include individual controls (dummy for being married, work experience and work experienced squared), occupation dummies, and firm fixed effects. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Literacy and numeracy scores are standardized. Instruments used for identification of switching model: mother has no formal education and monthly household income. Switching model estimated using a two-step model. The difference in sample size between column 1 and columns 2 and 3 is due to some missing values in the identifying variable 'household income'.

Table A.7 – Log earnings regressed on cognitive and non-cognitive skills and determinants of hours worked per week – OLS

	Log current earnings					Hours worked
	(1)	(2)	(3)	(4)	(5)	(6)
Years of education	-0.016**	-0.010*	-0.023***	-0.028***	-0.028***	-0.056
	(0.007)	(0.005)	(0.006)	(0.005)	(0.005)	(0.133)
Years of education (sqrd)	0.004***	0.004***	0.004***	0.003***	0.003***	-0.008
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
OP (std)	0.007	0.005	0.006	0.003	0.003	0.061
	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.153)
CO (std)	-0.005	-0.015*	-0.018**	-0.017**	-0.017**	0.273
	(0.011)	(0.009)	(0.009)	(0.008)	(0.008)	(0.234)
EX (std)	-0.004	-0.006	-0.003	-0.000	-0.000	-0.220
	(0.011)	(0.007)	(0.007)	(0.007)	(0.007)	(0.214)
AG (std)	0.003	0.012**	0.012**	0.009*	0.009*	-0.057
	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)	(0.195)
ES (std)	0.015	0.010	0.010	0.011	0.011	0.070
	(0.012)	(0.009)	(0.009)	(0.008)	(0.008)	(0.203)
HAB (std)	0.001	-0.004	-0.004	-0.006	-0.006	0.282*
	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.147)
GR (std)	0.017*	0.009	0.008	0.005	0.005	0.278
	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.175)
Reading score			0.040***	0.033***	0.033***	-0.147
			(0.011)	(0.011)	(0.011)	(0.251)
Numeracy score			0.018*	0.018*	0.018*	0.597**
			(0.010)	(0.010)	(0.010)	(0.260)
Indvl controls	YES	YES	YES	YES	YES	YES
Firm fixed effects		YES	YES	YES	YES	YES
Occupation dummies				YES	YES	YES
N	4,678	4,678	4,678	4,678	4,678	4,678
R^2	0.446	0.492	0.497	0.548	0.548	0.036

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are a dummy for being married, work experience and work experienced squared. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Literacy and numeracy scores are standardized.

Table A.8 – Probability of being hired through different hiring channels: marginal effects after multinomial logit

Being hired through	Formal (1)	Family (2)	Friends (3)	Village (4)
Years of education	0.042***	-0.013*	-0.011	-0.018***
	(0.014)	(0.008)	(0.008)	(0.006)
Years of education (sqrd)	0.000	-0.000	-0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)
OP (std)	-0.000	-0.009	-0.002	0.012*
	(0.013)	(0.011)	(0.010)	(0.007)
CO (std)	-0.008	-0.000	0.009	-0.001
	(0.018)	(0.012)	(0.013)	(0.009)
EX (std)	0.009	-0.003	-0.015	0.009
	(0.016)	(0.012)	(0.011)	(0.009)
AG (std)	-0.004	0.015	-0.010	-0.002
	(0.012)	(0.009)	(0.008)	(0.006)
ES (std)	-0.023	0.023*	-0.008	0.008
	(0.016)	(0.013)	(0.012)	(0.009)
HAB (std)	0.010	0.000	0.010	-0.020***
	(0.012)	(0.008)	(0.008)	(0.006)
GR (std)	0.010	0.033***	-0.031***	-0.012
	(0.013)	(0.010)	(0.009)	(0.008)
Reading score	0.079***	-0.054***	-0.029**	0.004
	(0.022)	(0.014)	(0.014)	(0.009)
Numeracy score	-0.022	0.022*	0.002	-0.002
	(0.020)	(0.012)	(0.011)	(0.008)
Mother no formal educ	-0.132***	0.030*	0.052***	0.050***
	(0.027)	(0.017)	(0.018)	(0.015)
HH inc: 5,000-7,500tk	0.135	-0.062	-0.044	-0.029
	(0.087)	(0.044)	(0.046)	(0.033)
HH inc: 7,501-10,000tk	0.162*	-0.039	-0.082*	-0.040
	(0.088)	(0.045)	(0.047)	(0.036)
HH inc: 10,001-15,000tk	0.151*	-0.086*	-0.029	-0.036
	(0.090)	(0.045)	(0.046)	(0.037)
HH inc: 15,001-20,000tk	0.118	-0.095*	0.003	-0.026
	(0.093)	(0.049)	(0.050)	(0.037)
HH inc: 20,001-30,000tk	0.254***	-0.061	-0.106*	-0.087*
	(0.098)	(0.057)	(0.060)	(0.051)
HH inc: 30,001-50,000tk	0.086	-0.033	-0.032	-0.021
	(0.122)	(0.068)	(0.072)	(0.064)
HH inc: 50,001tk and above	1.334***	-2.371***	0.685***	0.352***
	(0.190)	(0.128)	(0.148)	(0.087)
Indvl controls	YES	YES	YES	YES
Occupation dummies	YES	YES	YES	YES
Firm characteristics	YES	YES	YES	YES
Observations	4,655	4,655	4,655	4,655
Pseudo R^2	0.219	0.219	0.219	0.219

Notes: Standard errors are bootstrapped (200reps) and clustered at the firm-level; *** $p<0.01$, ** $p<0.05$, * $p<0.1$; Marginal effects reported are at the means of covariates. The hiring channel 'politics and school' has been combined with the hiring channel 'family' due to the small number of observations in the former and this being suggested by a Wald test of whether two outcomes can be combined. Individual controls experience, experience squared, and a dummy for being married. Firm characteristics include industry, firm size, a dummy for exporting firms, and the gender of the CEO. Personality traits are acquiescence corrected. Literacy and numeracy scores are standardized. The table reports marginal effects at means of covariates.

Table A.9 – Endogenous switching model. Second stage of log hourly wages regressed on cognitive and non-cognitive skills and interactions with being a white collar worker

Log hourly current wage	Formal (1)	Networks (2)
Reading score	0.066**	-0.033**
	(0.028)	(0.014)
Numeracy score	-0.014	0.022**
	(0.026)	(0.011)
Reading score # white collar	-0.061*	0.064***
	(0.032)	(0.019)
Numeracy score # white collar	0.018	-0.024
	(0.029)	(0.017)
OP (std)	0.032	-0.021*
	(0.021)	(0.011)
CO (std)	0.009	-0.003
	(0.028)	(0.014)
EX (std)	0.010	-0.004
	(0.024)	(0.012)
AG (std)	-0.012	0.011
	(0.022)	(0.010)
ES (std)	-0.046*	0.014
	(0.026)	(0.014)
HAB (std)	-0.000	-0.022**
	(0.022)	(0.009)
GR (std)	-0.011	0.016
	(0.022)	(0.011)
OP (std) # white collar	-0.007	0.016
	(0.023)	(0.015)
CO (std) # white collar	-0.042	-0.031
	(0.030)	(0.020)
EX (std) # white collar	-0.005	0.012
	(0.027)	(0.017)
AG (std) # white collar	0.029	-0.001
	(0.024)	(0.015)
ES (std) # white collar	0.063**	0.010
	(0.030)	(0.020)
HAB (std) # white collar	-0.028	0.019
	(0.024)	(0.014)
GR (std) # white collar	-0.002	-0.028*
	(0.024)	(0.015)
Indvl controls	YES	YES
Occupation dummies	YES	YES
Firm fixed effects	YES	YES
Inverse Mills ratio	-0.234***	0.133***
	(0.051)	(0.047)
N	4,655	4,655

Notes: Standard errors clustered at the firm-level in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Individual controls are education, education squared, a dummy for being married, work experience and work experienced squared. OP = openness to experience; CO = conscientiousness; EX = extraversion; AG = agreeableness; ES = emotional stability; HAB = hostile attribution bias; GR = grit; Personality traits are acquiescence corrected. Literacy and numeracy scores are standardized. Instruments used for identification: mother has no formal education and monthly household income. White collar occupations: managers, professionals, clerks, service and sales workers. Estimated using a two-step model.

Table A.10 – Returns to skills using an endogenous switching model - Multiple hiring channels

Log hourly wages	Formal (1)	Family (2)	Friends (3)	Village (4)
Years of education	-0.049	-0.035	-0.028	-0.061*
	(0.030)	(0.029)	(0.028)	(0.035)
Years of education (sqrd)	0.003***	0.002	0.002	0.005**
	(0.001)	(0.002)	(0.002)	(0.002)
OP (std)	0.019	-0.016	-0.007	-0.005
	(0.018)	(0.039)	(0.034)	(0.050)
CO (std)	-0.003	0.002	-0.011	-0.042
	(0.019)	(0.036)	(0.034)	(0.046)
EX (std)	0.028	0.036	0.027	0.029
	(0.022)	(0.040)	(0.037)	(0.064)
AG (std)	0.003	0.014	0.037	0.032
	(0.015)	(0.034)	(0.026)	(0.038)
ES (std)	0.008	0.071	0.071*	0.060
	(0.025)	(0.046)	(0.041)	(0.054)
HAB (std)	-0.030	-0.033	-0.022	-0.014
	(0.020)	(0.043)	(0.038)	(0.077)
GR (std)	-0.014	0.037	0.079	0.035
	(0.026)	(0.059)	(0.048)	(0.067)
Reading score	0.031	-0.024	-0.050	-0.094
	(0.051)	(0.076)	(0.056)	(0.091)
Numeracy score	-0.027	0.010	0.013	0.113*
	(0.031)	(0.041)	(0.035)	(0.058)
Indvl controls	YES	YES	YES	YES
Occupation dummies	YES	YES	YES	YES
Selection variables	YES	YES	YES	YES
Firm characteristics	YES	YES	YES	YES
$\rho 1$	-0.403*	-0.807	0.077	-0.393
	(0.220)	(0.640)	(0.365)	(0.571)
$\rho 2$	0.365	0.469	1.412**	1.344
	(0.924)	(0.378)	(0.630)	(0.992)
$\rho 3$	-0.868	-0.793	-0.070	-0.491
	(0.927)	(0.802)	(0.280)	(1.078)
$\rho 4$	1.475	1.313	1.329	0.109
	(1.028)	(1.067)	(0.861)	(0.407)

Notes: Standard errors are bootstrapped (200reps) and clustered at the firm-level; *** p<0.01, ** p<0.05, * p<0.1; Individual controls include experience, experience squared, and a dummy for being married. Firm characteristics include industry, firm size, a dummy for exporting firms, and the gender of the CEO. Personality traits are acquiescence corrected. Numeracy and literacy scores are standardized. Instruments used for selection identification are education of the mother and monthly household income. Selection corrected using Bourguignon et al. (2007).

Table A.11 – Characteristics of firms used in wage gap analysis sample

Sample	Sample 1	Sample 2	Sample 3
Used for	OLS regressions	Selection correction with firm fixed effects	Decomposition of within firm wage gap
Restrictions	Male & non-missing NC	Same as (1)	Same as (1)
Hiring channels	all	≥ 1 formal & network	≥ 2 formal & network
Percentage of firms	(1)	(2)	(3)
Commerce	0.150	0.147	0.157
	(0.36)	(0.36)	(0.37)
Education	0.154	0.194	0.192
	(0.36)	(0.39)	(0.39)
Finance	0.148	0.159	0.157
	(0.36)	(0.37)	(0.37)
Manufacturing	0.396	0.368	0.401
	(0.49)	(0.48)	(0.49)
Public administration	0.152	0.132	0.093
	(0.36)	(0.34)	(0.29)
At most 20 employees	0.376	0.260	0.169
	(0.48)	(0.44)	(0.38)
21 - 70 employees	0.236	0.271	0.285
	(0.43)	(0.45)	(0.45)
More than 70 employees	0.3888	0.469	0.547
	(0.49)	(0.50)	(0.49)
Firm located in Dhaka	0.528	0.609	0.657
	(0.50)	(0.49)	(0.48)
Main channel of job advert: networks	0.331	0.217	0.192
	(0.47)	(0.41)	(0.39)
One channel of job advert: networks	0.536	0.481	0.477
	(0.05)	(0.50)	(0.50)
Total number of firms	487	258	171

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS). Sample 1 represents the sample used for the initial OLS regressions. Sample 2 represents the sample of firms used for the endogenous switching model including firm fixed effects. Sample 3 is the sample used for the decomposition of the within-firm wage gap.

Figure A.2 – Within firm wage gap

(a) Distribution of wage gap (b) Wage gap by industry