Non-cognitive skills, social networks and labor market outcomes in Bangladesh

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Abstract

This paper uses a novel matched employer-employee data set from Bangladesh, representing the formal sector, to estimate the relative importance of non-cognitive skills and the interplay between skills and hiring channels in determining labor market outcomes. Our estimates of returns to schooling are positive and convex. Including cognitive skills (literacy and numeracy tests) and non-cognitive skills (the Big Five personality test) shows that literacy and agreeableness each have significantly positive effects on wages of approximately the same degree. We further find heterogeneous effects of personality traits on earnings which differ by hiring channel. Firm characteristics can help explain part of the differential returns to skills: employers who value team-work and problem-solving skills are associated with a smaller wage gap between workers who found their jobs through formal and informal hiring channels.

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1 Introduction

Human capital, the stock of all knowledge, competences, and personality attributes that enable a worker to be more productive, has long been recognized as a driver of economic growth in both developed and developing countries. The impact of education, experience, and on-the-job training on wages and other labor market outcomes has been a widely discussed phenomenon since Becker's (1964) and Mincer's (1974) groundbreaking studies. 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; this rate is even higher in low-income developing countries. However, focusing on returns to education only ignores the innate multidimensionality of the concept of human capital, which also comprises cognitive ability, non-cognitive skills, and vocational skills. Cognitive skills refer in a general sense to skills associated with intelligence and ability; they build the foundations for acquiring new skills throughout life. Non-cognitive skills, on the other hand, are based on one's personality rather than intellect and facilitate interaction and communication with others, while vocational skills are task-specific skills particular to a certain occupation or line of work (World Bank 2012).

Cognitive skills have often been approximated via standardized test scores in developed countries and literacy rates as well as numeracy tests in developing countries. Hanushek and Woessmann (2008) focus on the direct effect of cognitive skills as compared to education and 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. Lee and Newhouse (2012), using the same database, find that, on the contrary, years of education remain important in determining labor market outcomes. Green and Riddell (2002) also find that including cognitive skills (literacy) in the earnings function reduces the measured impact of schooling, as well as the more general assessment that literacy and schooling do not seem to interact in further influencing earnings. Hanushek et al. (2013) use a cross-country data set and find that returns are largest to numeracy and literacy skills and smaller for problem-solving skills. However, assessing the differential impacts of years of schooling and cognitive skills on earnings is not without problems. Griliches (1977) demonstrates that including further control variables such as intelligence testing to control for ability could worsen rather than improve their inherent bias, as these ability tests are themselves subject to measurement error. Cawley et al. (2001) also point to the difficultly of measuring cognitive skills; 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.

Economic literature has only recently started to include non-cognitive skills like personality traits and behaviors 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 proficiency in subjects learned in school. Indeed, non-cognitive skills have been found to be strongly associated with higher earnings and seem to have a positive effect on earnings beyond the effect of pure cognitive ability (Heckman et al. 2006). Mueller and Plug (2006) show that the effect of personality traits on earnings is of similar magnitude to that of cognitive skills. Further, personality has been shown to be an important predictor of labor market outcomes (Heineck and Anger 2008; Borghans et al. 2008), but the relative importance of various personality traits differs. Conscientiousness has been shown to be associated with job performance (Nyhus and Pons 2005) and plays an important role in determining job performance and wages alongside traits related to emotional stability (Drago 2011). However, mostly due to data availability, research on returns to cognitive and especially 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 skills such as literacy and numeracy. In Peru, Díaz et al. (2012) find that returns to the socio-emotional trait of perseverance are as high as returns to average cognitive ability.

The impact of the different components of human capital on labor market outcomes is further likely to differ depending on the job search methods employed by an individual to obtain a job in the first place. If individuals self-select into different channels of job search depending on their human capital, the hiring channel could then mitigate its impact on wages. This could be particularly important in developing countries, where formal institutions are traditionally weak and the informal hiring channel is employed frequently for job searches (Fafchamps 2006). 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 informal 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). According to this line of thought, jobs obtained via social networks should result in higher wages. Having to use informal networks to find a job can also be perceived as a negative signal to employers, however, as those relying on social 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 results are equally mixed, with some studies supporting a positive relationship between informal job searches and wages (e.g. Kugler 2003; Simon and Warner 1992) while others suggest a negative one (e.g. Bentolila et al. 2004; Berardi 2013).

This paper uses a novel matched employer-employee data set from Bangladesh, representing the formal sector, to estimate the relative importance of non-cognitive skills and the interplay between skills and hiring channels in determining labor market outcomes. Informal search methods are found to be used predominantly by less educated workers of a lower socio-economic status (Topa 2011), but the role of cognitive ability and personality in the usage of informal networks is less clear. Lee and Newhouse (2012) 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. However, Beaman and Magruder (2012) provide evidence that, while high-ability individuals do have the ability to screen their networks and are able to successfully identify individuals with similarly high levels of ability, they tend to refer those in their networks only when properly incentivized to do so. Caliendo et al. (2014) provide evidence that non-cognitive skills also play a role in influencing job search; they find that individuals with an internal locus of control exert higher search effort.

Few studies on the effect of the different components of human capital are conducted in the context of low-income, developing countries like Bangladesh. Asadullah (2006) provides the first reliable estimates of the economic returns to formal education in Bangladesh, using a national household survey from 1999-2000 to focus on wage-workers only. He finds that returns are higher in urban than in rural areas (8.1 percent vs. 5.7 percent) and higher for females than males, which is broadly in line with Psacharopoulos and Patrinos' (2004) review. No study has previously looked at the effect of cognitive and non-cognitive skills separately, however, further considering the potentially mitigating effect of the hiring channel.

We find that that reading skills have a positive effect on mean wages, even when controlling for educational attainment. Numeracy, however, is not found to have an effect. Effects of personality on wages differ by hiring channel: estimating separate wage regressions for those hired formally and informally, we find that extraversion, openness to experience, and agreeableness have a positive effect on wages for those hired formally. We incorporate the fact that the same unobserved characteristics could drive the selection of the hiring channel as well as the wage through an endogenous switching model and still find that openness to experience has a positive effect on wages for those who found their job through formal job search methods. We further model the selection process as a multinomial logit model as workers face not only a choice between formal and informal hiring channel, but also between types of informal hiring channels (friends, family, or connections within the village). We find that the personality traits have different effects on predicting the probability of having chosen a certain hiring channel. A higher level of agreeableness, for example, increases the probability of having found the job via family connections, while higher conscientiousness has a similar effect for the likelihood of having found jobs through friends. Correcting for this potential self-selection, we find that openness to experience remains to have a positive effect on wages for workers hired through the formal channel, while the impact of personality attributes varies by type of informal channel used.

Lastly, we try to understand whether firm characteristics can help explain part of the differential returns to skills. We find that employers who value team-work and problem-solving skills more are associated with a smaller wage gap between workers who found their job through formal or informal hiring channels.

The remainder of this paper is organized as follows: section 2 presents the methodology used, section 3 describes the data, section 4 presents main results, and section 5 concludes.

2 Methodology

The empirical analysis starts from Mincer type regressions to provide a first estimate of the returns to schooling, comparable with those found in literature, followed by the inclusion of measures for cognitive as well as non-cognitive skills in the wage regressions. We continue by investigating the link between personality and the type of hiring channel, to understand whether it mitigates or enhances returns to non-cognitive skills. As the use of the hiring channel is likely to be endogenous, we take into account the self-selection using an endogenous switching model as well as a multinomial logit selection correction model.

2.1 *Returns to different skills*

The empirical framework follows a basic Mincer specification where labor market outcomes are regressed on a set of demographic characteristics, as well as cognitive and non-cognitive skills:

$$lnw_{ij} = \beta_0+\beta_1 X_i+\beta_2 Educ_i+\beta_3 Cognitive_i+\beta_4 Perso_i + \epsilon_{ij} + \phi_j \qquad (1)$$

where lnw_i is the natural logarithm of the hourly current wage rate for individual *I, X* is a vector of demographic characteristics, *Educ* is a vector of variables relating to formal education. Returns to education especially in developing countries might be non-linear (see for example Söderbom et al. 2006). We follow Card (1999) in relying on a simplified model, which builds on a linear schooling term and a low-order polynomial, since such a model is already able to explain a substantial amount of the variation in observed earnings data. *Cognitive* is a vector of cognitive skills, the score of the individual on numeracy and literacy tests, *Perso* is a vector of non-cognitive skills, standardized scores on the five dimensions of the Big Five personality assessment (Openness to Experience, Conscientiousness, Extraversion, Agreeableness, and Emotional Stability), ϕ is a firm fixed effect, and ϵ is the error term.

We estimate the model both with and without firm fixed effects to allow or control for unobserved heterogeneity due to firm characteristics that could influence firm-level determinants of wages. The importance of employer characteristics in wage-setting has been shown by Groshen (1991), Abowd et al. (1999), and Bryan (2004). Including proxies for ability and personality in the wage regressions is potentially dangerous, if the proxies themselves are able to partially control for the omitted factors (ability, personality), but are also simultaneously affected by the variable of interest (years of education) (Angrist and Pischke 2009).

2.2 *Skills and the type of hiring channel*

Further, in order to understand whether and to what extend returns to different skills are mitigated by the choice of the hiring channel we estimate an endogenous switching model. This model explicitly takes into account the fact that the choice of hiring channel might be endogenous to the same characteristics that drive wage setting. This would lead to sample selection if, for example, less able or more neurotic workers find their job through informal channels such as friends and family. Once employed in the job, this worker could then earn less due to his lower innate ability, due to having been hired through informal channel, or a combination of the two. At the same time, the hiring channel might affect the impact of wage determinants. The endogenous switching model is able to correct for both the endogenous sample selection and the switching impact of wage determinant and has been employed to investigate informal hiring channels in Delattre and Sabatier (2007) in the case of France and in Berardi (2013) in the case of Senegal.

The switching model structure can be outlaid as follows:

$$lnw_{ij}^{F} = \beta_0^F + \beta_{employee}^F A_i + \beta_{firm}^F B_j + \epsilon_{ij}^F \quad (2)$$
$$lnw_{ij}^{I} = \beta_0^I + \beta_{employee}^I A_i + \beta_{firm}^I B_j + \epsilon_{ij}^I \quad (3)$$

where $lnw_{i,j}^F$ is the natural logarithm of the hourly wage rate of worker *i,* hired through formal channels, $lnw_{i,j}^I$ the natural logarithm of the hourly wage rate of worker *i* hired through informal channels, A_i is a vector of worker *i*'s characteristics, B_j is a vector of firm *j*'s characteristics, and $\varepsilon_{i,j}^F$ and $\varepsilon_{i,j}^I$ are the error terms for formal and informal hires, respectively.[1]

However, 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 informally. An individual *i* therefore engages in informal job search (*INF*) if:

$$INF_{ij}^{*} = \gamma Z_{ij} + u_{ij} > 0 \quad (4)$$

[1] The model is also estimated with firm fixed effects instead of B_j, the vector of firm *j*'s characteristics.

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

$$INF_{ij} = \begin{cases} 1 & if \;\; INF_{ij}^{*} > 0 \\ 0 & if \; not \end{cases} \tag{5}$$

The available data already allows us to control for many observable characteristics at the worker and firm level. Still, individuals choosing to engage in their job search informally and those choosing to use formal channels might differ in unobserved characteristics. To grasp the aspect of size of network on informal job search, we use “mother has no formal education” as an instrument, to approximate for the type of network that an individual has at her disposal, which might further influence its expected use. Under the assumption that networks tend to be founded among similar people, the type and expected value of a job obtained through the social network of a mother without formal education will be quite different from the one available through the network of a mother with formal education, which will influence a child’s decision to search via her mother’s network or not.

While the distinction between the formal and informal hiring sector is an important one, it is also well-understood that the type of informal network used matters (Granovetter 1973). To investigate whether returns to skills vary by the type of informal network used for successful job search and whether personality types can help predict the probability of using one type of social network versus another we further use a multinomial selection correction model to account for four different types of hiring channels: one formal channel, and three informal channels (family, friends, and the village). Hence, we estimate returns to skills when selection is based on a multinomial logit model. The structure is similar to the endogenous switching model outlaid previously, except that instead of outcome equations (2) and (3), we now have four equations, one for each category (formal, family, friends, and the village) and can again observe whether the individual used this network as of one her job search methods.

2.3 *Determinants of the within-firm formal – informal wage gap*

Lastly, we aim to see to what extend firm characteristics can help explain the within-firm wage gap between formal and informal hires, for example because firms value some skills more in formal hires than in informal ones. We are using a hierarchical modeling approach (Bryk and Raudenbush 1992), also applied in Meng (2004), Nordman and Wolff (2009) and Nordman et al. (2015), to capture the determinants of the within firm informal hiring channel wage gap. Wage equations for formal and informal hires are then estimated separately including firm fixed effects (i.e. equation (1) is estimated separately for formal and informal hires):

$$lnw_{ij}^F = \beta_0^F + \beta_1^F X_i + \beta_2^F Educ_i + \beta_3^F \, Cognitive_i + \beta_4^F \, Perso_i + \epsilon_i^F + \phi_j^F \tag{6}$$

$$lnw_{ij}^I = \beta_0^I + \beta_1^I X_i + \beta_2^I Educ_i + \beta_3^I \, Cognitive_i + \beta_4^I \, Perso_i + \epsilon_i^I + \phi_j^I \tag{7}$$

The regressions above control for workers socio-economics characteristics and skills. The effect of the firm fixed effect, ϕ, thus reflects a premium paid by the firm to its employees. The difference between ϕ^F and ϕ^I can hence be interpreted as an estimate of the within firm wage premium/penalty for having been hired through informal channels. We then use OLS regressions to estimate the effect of firm level characteristics on this within firm wage gap.

3 Data

This study is based on the 2012 Bangladesh Enterprise-Based Skills Survey (ESS)[2], a matched employer-employee survey commissioned by the World Bank as part of the Bangladesh Education Sector Review with the aim to assess whether the education system in Bangladesh is producing graduates with skills relevant to and demanded by its labor market (Nomura et al. 2013).[3] The survey covers the formal sector. Returns to education and cognitive skills are further likely to vary between formal and informal sectors, an issue especially vital in developing countries, where the informal sector is very prominent. Arguably, returns to education are higher in the formal than in the informal sector (Bennell 1996). Unfortunately, the data available covers the formal sector only. Therefore, we are able to account for neither returns varying by formality nor selection effects (selection into employment or even into the formal versus informal sector).

The survey unit of the ESS is the firm; the survey consists of two modules, one each for employer and employee. Responses for the employer module come from business owners and high-level managers; its questions deal with information on recruitment and training of employees, as well as an assessment of the workplace and firm performance. The employee part of the survey is conducted for a sub-sample of employees in the sampled firms.[4] It contains detailed information of each individual's educational background and numeracy and literacy skills measured by an objective test, as well as a personality self-assessment. The employee survey also asks workers how they found their current job. Formal channels include media

[2] All tables in this study are based on our own calculations using the 2012 Bangladesh Enterprise-Based Skills Survey (ESS) unless stated otherwise.
[3] Nakata and Nomura (2015) use the same data set and analyze the decomposition of the wage gap between informally and formally recruited workers.
[4] Every 3rd person in a small firm; every 5th and 7th person in a medium and large firm; and if employment exceeds 200, every 30th person is interviewed (Nomura et al. 2013).

advertising, school placement, public and private employment services, job fairs, and internet posting. Informal channels include family or relatives, friends, political affiliation, school alumni, and people from same village or town.

Measures for numeracy and literacy stem from questions of the National Student Assessment conducted by the Bangladeshi Department of Primary Education (Nomura et al. 2013), designed to assess skills that workers who have completed primary school should possess. This test is administered to all workers, regardless of whether or not they have completed primary education. Personality measures included in the wage regressions are based on the "Big Five" typology of personality tests. The Big Five are a widely used list of key traits, which are understood to capture the broadest level of personality traits (see McCrae and Costa 2008)[5]. The Big Five contain five personality traits: (1) Openness to Experience, closest to pure intellect, this trait is capturing one's tendency to be open to new experiences (aesthetic, cultural or intellectual); (2) Conscientiousness describes one's tendency to be organized, hardworking, responsible; (3) Extraversion encompasses directing one's interest towards the outer world of people and things; (4) Agreeableness is the tendency to act cooperatively and in an unselfish manner; and (5) Neuroticism (or Emotional Stability) is a chronic level of emotional instability and proneness to psychological distress (or if taken as Emotional Stability, the predictability and consistency in emotional reactions with absence of rapid mood changes). The short Big Five Inventory (BFI-S) was included in the survey (containing three different questions per personality dimension). This shortened version of the original questionnaire was originally developed by John and Srivastava (1999) and has been validated in large panel survey such as the German Socio-Economic Panel Survey.[6]

The survey covers firms in five sectors: manufacturing, commerce, finance, education, and public administration. In total, the sample contains 500 firms and 6,981 individuals, stratified by economic sector and firm size: small (less than 20 employees), medium (21-70), and large (71+). Despite being limited to these 5 sectors, the survey is quite representative of employment in the Bangladeshi formal sector, as these sectors cover 87 percent of employment and 91 percent of formal sector employment in Bangladesh (Nomura et al. 2013).

[5] The Big Five factor model is usually attributed to Allport and Odbert (1936) who theorize 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).

[6] Almlund et al. (2011) discuss how using previously measured traits as predictors of later outcomes can lead to errors in variables problem if the traits evolve over time. However, psychological research has demonstrates the stability of personality traits beginning in young adulthood (Mischell and Shoda 2008) and economic research has recently shown that personality traits of working age Australian adults are stable over a four-year period (Cobb-Clark and Schurer 2011).

The survey further contains information on the firms themselves, answered by senior management, which are used to estimate the determinants of the within-firm wage gap for informal workers. The employer part of the survey contains information on whether informal advertising is the main channel of publishing a job, the importance of certain selection criteria for hiring professionals or non-professionals (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 managers/professionals and non-professionals (such as team working, problem solving or motivation).

4 Results

3.1 *Descriptive statistics*

Results for this paper are based on a sample that is restricted to firms that have at least two formal and two informal hires, leaving us with 244 firms, 1,961 formal hires and 1,840 informal hires. Table 1 presents some characteristics of the restricted sample used in the remainder of this paper in comparison to the original sample of formal firms. As can be seen in Table 1, while in the original sample firms are distributed in approximately equal shares among the size categories, the restricted sample is skewed towards larger firms, with manufacturing still being overrepresented. The majority of firms is located in the capital district, Dhaka. Looking at potential channels of hiring, fewer firms of the restricted sample state that their main method of advertising a vacancy is through informal networks. Still, the share of firms that use informal advertising channels as at least one mode of announcing a vacancy is similar among the original and restricted sample (around half).

Table 2 presents the characteristics of a random sample of employees within those firms. Employees of the restricted sample are very similar to those of the original sample. Most workers surveyed are male and on average 30 years old with 5 years of work experience at their present job. On average, employees only had two years of experience prior to entering their current jobs, suggesting rather low job mobility. Most of the sampled workers occupy lower-income occupational categories, such as clerking, construction, and unskilled occupations. The majority of firms and workers are located in Dhaka, the capital. Workers have an average of 10 years of education. They score worse on the literacy test than on the numeracy test, and score lowest on the personality trait openness to experience, and highest on agreeableness.[7] A slight majority of workers obtained their current job via informal networks.

[7] Workers of the restricted and the original sample perform differently on the personality test. Workers included in the restricted sample score significantly in terms of openness to experience, and emotional stability, but better in all other categories. However, only agreeableness is statistically different between the two samples.

3.2 *Returns to skills*

We first estimate OLS regressions with the log of the current hourly wage as the dependent variable and a basic set of covariates that is subsequently expanded. The first set of socio-economic covariates consists of years of education, experience prior to joining the firm, tenure in the current firm (as well as quadratic effects for these three variables), a dummy variable for being female and the cognitive variables described above: standardized scores on numeracy and literacy tests. We continue by including a second set of variables, standardized personality test scores for each of the Big Five personality traits (Openness to Experience, Conscientiousness, Emotional Stability, Agreeableness, and Extraversion). Lastly, we include firm fixed effects in order to take into account unobserved firm heterogeneity that could have an influence on wages (results are displayed in Table 3). We find that returns to education are convex. Reading skills are found to have a positive influence on wages, even when controlling for educational attainment. Numeracy is not found to have an effect at all, however. Including the standardized personality test scores does not provide a clear picture; when first introduced, openness to experience has a positive effect on wages which is bigger than the effect of literacy, but once we introduce firm fixed effects, it is instead agreeableness that has a significant positive effect on wages. Figure A.1 (Appendix) demonstrates the wage dispersion by hiring channel. In order to also consider differential effects of skills on wages depending on the hiring channel, we then estimate the regressions described above separately for those who were hired through the formal hiring channels and those who found their job via informal networks (Table 4). Results already indicate a differential effect; while returns to education are increasing in both channels, returns to cognitive skills (literacy) as well as non-cognitive skills are only significant in the formal hiring channel.

3.3 *Skills and an endogenous hiring channel*

Since results indicate differential returns to skills depending on the hiring channel, we continue by estimating an endogenous switching model to better understand the heterogeneous effects, as well as to explicitly take into account the fact that the choice of hiring channel might be endogenous to the same characteristics that determine wage-setting. We start with the same specification as in previous regressions (socio-economic characteristics, cognitive skills, and non-cognitive skills) and next add firm characteristics (industry dummies and firm size) and dummy variables for occupation, which are necessary because wages within the same firm could differ by occupation. Heckman et al. (2006) have shown that individuals sort into occupations and education based on their personality so our estimate of returns to personality could be overestimated if it only captures occupational effects. However, occupational assignment could also be the result of an employer's preferences rather than differences in individual choice or productivity (Albrecht et al. 2003). In the endogenous switching model 'mother has no formal education' is used as exclusion restriction for engaging in informal job search under the assumption that once education, cognitive skills, and non-cognitive skills have been controlled for, ‘mother has no formal education’ can be legitimately excluded from the wage regressions.

Table 5 presents the results of the endogenous switching model. The first column depicts the selection equation (equation 5 from above), the second column the wage regression for the formal hiring channel (equation 2 from above) and the third column the wage regression for the informal hiring channel (equation 3 from above). Educational attainment is increasing and significant in all three equations. The reading score has a negative effect in the selection equation, but is insignificant in the wage equations; the numeracy score remains insignificant in all equations. Looking at personality shows that conscientiousness and emotional stability have a positive effect on the probability of finding a job through informal networks, though the latter is only significant once we control for firm characteristics and occupation dummies. Given the hiring channel, openness to experience has a positive influence on wages for those who are hired formally, but no personality trait is found to have an effect on wages for those hired through informal channels.

In order to better understand the role of personality attributes for those hired through informal channels, we further disaggregate the informal hiring channel into its types, namely whether the worker found his job through her family, her friends, or her village connections. Table 6 displays a multinomial logit model, estimating the probability of having chosen a specific hiring channel. Panel A displays the regression outcomes and Panel B shows marginal effects. Table 6 illustrates the differential effect of non-cognitive skills on the probability of choosing one of the informal hiring channels. Agreeableness is positively associated with a higher likelihood of having found the job through family members. This personality trait however, does not seem to play a role for those who found their job through other forms of informal job search. Instead, higher conscientiousness, the tendency to be organized and hardworking, increases the probability of having found a job through friends, whereas a higher test score on emotional stability has a similar effect for hires through village connection. This differential effect of the different personality traits in the subgroups of the informal hiring channel variable helps to understand their insignificance when grouped together as one single variable.

Having the differential effect of personality traits depending on the type of informal hiring channel in mind, Table 7 presents the returns to the different skills by hiring channel. However, instead of a simple dichotomous selection into either the formal or informal hiring channel (as modeled earlier), selection in this case is specified as a multinomial logit model. We chose the selection correction put forward in Bourguignon et al. (2007), relying on a generalized version of the Dubin-McFadden correction. The first column presents the returns to skills in the formal hiring channel, in which both openness to experience and conscientiousness are found to have significantly positive effects. This positive and significant effect of openness to experience (and to a lesser degree of conscientiousness) on wages for those who found their jobs through formal job search methods has been found consistently throughout this paper. Among those who found their jobs through family networks, conscientiousness exhibits a positive effect on wages; for those who used friends, openness to experience has a positive impact, while a higher score on the emotional stability trait actually decreases wages. No personality trait is found to have an effect on wages for workers who found their jobs through village connections. The positive effect of openness to experience on wages persists after further controlling for firm characteristics and including occupation dummies.

3.4 *Determinants of the within-firm formal – informal wage gap*

The previous sections have shown that the different skill types do have different influences on wages and that their influence is mitigated by the hiring channel through which workers found their jobs. The purpose of this section is to identify whether the differential returns to skills depending on the hiring channel in fact reflect preferences of firms for different skill sets among different types of hires. To the degree to which employers value certain skills more and have underlying assumptions or information (for example, through informal networks or the formal hiring process) about the availability of these skills in different hiring types (formal/informal), this could affect the wage premium being paid to the different types of hires. This difference is captured by the differences in firm fixed effects.

We estimate OLS regressions with the difference in firm fixed effects from equations (6) and (7) above as the dependent variable. We start by including covariates capturing the characteristics of the firm, such as its industry, firm size, where recruitment decisions are being taken, whether the firm has a formal review process for each employee, and whether it provides on-the-job training, the gender of the top manager and the share of women among the top managers, the education of the top manager, and whether the company uses informal channels as their main hiring channel. Results are displayed in Table 8 and indicate that the wage gap between formal and informal workers decreases when informal channels are the main hiring channel, when firms are larger, and when recruitment decisions are taken at the firm's headquarters (compared to solely by this establishment).

We continue by including standardized scores capturing the importance the company places on different types of skills among its employees, as well as standardized scores dealing with the importance it places on different hiring criteria. These are included separately for professionals and non-professionals. Employers were asked (on a scale of 1-10) how important they think it is for their employees (non-professionals and managers being dealt with separately) to have the following skills: communication, team work, problem solving, literacy, numeracy, costumer care, responsibility, motivation, creativity, and vocational job-specific skills. They were also asked (on a scale of 1-10) how important the following criteria are for the hiring decision:

academic performance, work experience, skill set, interview, informal network/recommendation, and political affiliation.

Including the covariates for the importance of skills among employees and for the importance of hiring criteria shows a different pattern for professionals and non-professionals. Employers who value communication skills among professional workers tend to be associated with larger wage gaps, whereas those that value team-work skills and problem-solving skills tend to be associated with smaller wage gaps between formal and informal hires. Looking at non-professionals reveals that employers that value problem-solving skills are associated with smaller wage gaps, and those who value informal networks or recommendations when making their hiring decisions are associated with bigger wage gaps between workers who have been hired formally or informally.

5 Conclusion

This paper provided estimates for the returns to different types of skills (educational attainment, cognitive skills and non-cognitive skills) on the labor market using a novel matched employer-employee data set from Bangladesh. We further looked at the interplay between different skills and hiring channels in determining labor market outcomes, which is an important issue especially in developing countries in which the role of informal networks is large and research on the effects of non-cognitive skills scarce.

Our results show that cognitive skills, as measured by reading ability, have a positive effect on wages, even when controlling for educational attainment. Furthermore, effects of personality on wages differ by hiring channel; estimating separate wage regressions for those hired formally and informally, extraversion has a positive effect on wages for those hired formally. We estimate an endogenous switching model to incorporate the fact that the same unobserved characteristics could drive the selection of the hiring channel as well as the wage. This would lead to sample selection if, for example, less able or more neurotic workers find their job through informal channels such as friends and family. Once employed in the job, this worker could then earn less due to his lower innate ability, due to having been hired through informal channel, or a combination of the two. Openness to experience continues to a positive effect on wages for those who found their job through formal job search methods.

We then estimate use a multinomial logit model as workers face not only a choice between formal and informal hiring channel, but also between types of informal hiring channels (friends, family, or connections within the village). Our results show that different non-cognitive skills have a different effect on predicting the probability of having chosen a certain hiring channel. A higher level of agreeableness, for example, increases the probability of having found the job via family connections, while higher conscientiousness has a similar effect for the likelihood of having found jobs through friends. Correcting for this selection using a multinomial logit correction specification, we find that openness to experience remains to have a positive effect on wages for workers hired through the formal channel, while the impact of personality attributes varies by type of informal channel used. Lastly, we try to understand whether firm characteristics can help explain part of the differential returns to skills. Employers who value team-work and problem-solving skills more are associated with a smaller wage gap between workers who found their job through formal or informal hiring channels.

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Tables

Table 1 Characteristics of firms - reduced versus original sample

Number of firms	Original sample	Restricted sample
< 20 employees	188	45
21 - 70 employees	116	61
More than 70 employees	192	112
Industry: Commerce	74	30
Education	75	43
Finance	74	38
Manufacturing	198	76
Public administration	75	31
Firm located in Dhaka	261	136
Main channel of job advert: informal	167	41
One channel of job advert: informal	267	100
Total	496	218

Source: 2012 Bangladesh Enterprise Based Skills Survey (ESS)

Table 2 Characteristics of employees - reduced versus original sample

	Employees	Original sample (N=5,864)	Restricted sample (N=3,576)
	Log hourly current earnings	3.591 (0.606)	3.61 (0.616)
	Female	0.155 (0.362)	0.168 (0.374)
	Age	30.15 (8.382)	29.62 (8.16)
	Age at hiring (years)	25.12 (6.623)	24.81 (6.546)
	Previous experience (years)	2.006 (3.675)	1.997 (3.814)
	Tenure (years)	5.029 (4.987)	4.812 (4.53)
Occupation	Managers	0.039 (0.195)	0.0373 (0.189)
	Professionals	0.14 (0.347)	0.125 (0.33)
	Associate professionals	0.071 (0.257)	0.066 (0.248)
	Clerical support workers	0.159 (0.366)	0.174 (0.379)
	Service workers	0.09 (0.287)	0.0879 (0.283)
	Sales workers	0.013 (0.115)	0.011 (0.104)
	Skilled agricultural	0.002 (0.044)	0.00212 (0.046)
	Construction, craft	0.317 (0.465)	0.331 (0.471)
	Plan and machine operators	0.042 (0.201)	0.0413 (0.199)
	Elementary occupations	0.125 (0.330)	0.125 (0.331)
Region	Rajshahi	0.052 (0.222)	0.0143 (0.119)
	Khulna	0.025 (0.156)	0.0158 (0.125)
	Dhaka	0.715 (0.451)	0.778 (0.416)
	Chittagong	0.13 (0.336)	0.121 (0.326)
	Barisal	0.021 (0.143)	0.0138 (0.117)
	Sylhet	0.029 (0.169)	0.0331 (0.179)
	Rangpur	0.028 (0.166)	0.0242 (0.154)
Skills	Bangla literacy skills score	4.908 (2.559)	5.126 (2.447)
	Numeracy skills score	5.908 (1.986)	6.027 (1.94)
	Openness to Experience	7.465 (1.822)	6.429 (1.615)
	Conscientiousness	7.642 (1.814)	7.5 (1.791)
	Extraversion	6.419 (1.594)	7.707 (1.807)
	Agreeableness	7.375 (1.948)	7.84 (1.782)
	Emotional Stability	7.845 (1.811)	7.461 (1.883)
Networks	Found job via informal networks	0.53 (0.499)	0.505 (0.5)

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

Table 3 Returns to Skills

	Col.1	Col.2	Col.3	Col.4	Col.5
Years of Education	-0.022**	-0.023**	-0.040***	-0.017	-0.038***
	(0.011)	(0.011)	(0.009)	(0.011)	(0.009)
Years of Education squared	0.005***	0.005***	0.005***	0.004***	0.004***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Prior Experience	0.021*	0.018*	0.023**	0.010	0.015*
	(0.011)	(0.011)	(0.010)	(0.010)	(0.009)
Prior Experience squared	0.000	0.000	0.000	0.001	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure in current firm	0.034***	0.034***	0.036***	0.032***	0.034***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)
Tenure in current firm squared	-0.001**	-0.000**	-0.001***	-0.000**	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.056*	-0.058*	-0.083***	-0.034	-0.077***
	(0.032)	(0.032)	(0.028)	(0.032)	(0.026)
Reading Score	0.020***	0.018**	0.021***	0.019***	0.021***
	(0.007)	(0.007)	(0.006)	(0.007)	(0.006)
Numeracy Score	-0.009	-0.006	0.002	-0.006	0.002
	(0.009)	(0.009)	(0.008)	(0.009)	(0.007)
Extraversion		0.019	0.010	0.016	0.010
		(0.015)	(0.010)	(0.015)	(0.010)
Openness to Experience		0.035**	0.017	0.031**	0.013
		(0.015)	(0.012)	(0.015)	(0.011)
Conscientiousness		-0.003	-0.007	-0.002	-0.009
		(0.013)	(0.011)	(0.013)	(0.012)
Emotional Stability		-0.008	-0.006	-0.002	-0.000
		(0.015)	(0.010)	(0.015)	(0.009)
Agreeableness		-0.004	0.019*	-0.006	0.019**
		(0.017)	(0.010)	(0.017)	(0.009)
Firm fixed effects			YES		YES
Occupation dummies				YES	YES
Constant	3.024***	3.020***	3.034***	3.450***	3.637***
	(0.078)	(0.079)	(0.063)	(0.092)	(0.072)
Observations	3,576	3,576	3,576	3,576	3,576
R^2	0.465	0.469	0.494	0.496	0.538

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

Table 4 Returns to Skills by Hiring Channel

	Col.1 Informal	Col.2 Formal	Col.3 Informal	Col.4 Formal
Years of Education	-0.029**	-0.029*	-0.042***	-0.050***
	(0.013)	(0.018)	(0.011)	(0.019)
Years of Education squared	0.005***	0.005***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Prior Experience	0.013	0.019	0.018*	0.020
	(0.011)	(0.016)	(0.010)	(0.014)
Prior Experience squared	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.001)
Tenure in current firm	0.030***	0.035***	0.034***	0.035***
	(0.006)	(0.006)	(0.006)	(0.005)
Tenure in current firm squared	-0.000	-0.001**	-0.001***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.080*	-0.041	-0.088**	-0.075*
	(0.045)	(0.038)	(0.038)	(0.042)
Reading Score	0.008	0.022**	0.009	0.021**
	(0.008)	(0.011)	(0.007)	(0.010)
Numeracy Score	-0.008	-0.004	-0.001	0.001
	(0.011)	(0.012)	(0.008)	(0.012)
Extraversion	0.013	0.024	-0.008	0.031**
	(0.016)	(0.021)	(0.012)	(0.015)
Openness to Experience	0.022	0.046**	0.010	0.035**
	(0.017)	(0.022)	(0.013)	(0.018)
Conscientiousness	0.001	-0.001	-0.019*	0.006
	(0.017)	(0.017)	(0.011)	(0.018)
Emotional Stability	-0.001	-0.010	-0.017	-0.012
	(0.019)	(0.019)	(0.011)	(0.013)
Agreeableness	-0.007	0.003	0.007	0.030**
	(0.019)	(0.021)	(0.013)	(0.013)
Firm fixed effects			YES	YES
Constant	3.071***	3.102***	3.077***	3.170***
	(0.091)	(0.108)	(0.073)	(0.101)
Observations	1,755	1,821	1,755	1,821
R^2	0.366	0.423	0.416	0.462

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

Table 5 Returns to Skills using an Endogenous Switching Model

	Col.1 select	Col.2 Formal	Col.3 Informal	Col.4 select	Col.5 Formal	Col.6 Informal	Col.7 select	Col.8 Formal	Col.9 Informal
Years of Education	-0.109*	-0.116***	-0.018	-0.070	-0.096***	-0.025*	-0.065	-0.091***	-0.014
	(0.058)	(0.031)	(0.014)	(0.055)	(0.023)	(0.014)	(0.062)	(0.022)	(0.013)
Years of Education squared	-0.003	0.006***	0.003***	-0.004*	0.006***	0.005***	-0.004	0.005***	0.003***
	(0.003)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)
Prior Experience	-0.015	0.016	0.011	-0.013	0.016	0.009	-0.011	0.009	0.002
	(0.042)	(0.015)	(0.012)	(0.044)	(0.015)	(0.011)	(0.043)	(0.014)	(0.011)
Prior Experience squared	0.001	0.001	0.000	0.001	0.001	0.000	0.001	0.001	0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.000)
Tenure in current firm	-0.021	0.032***	0.028***	-0.011	0.035***	0.031***	-0.009	0.035***	0.027***
	(0.022)	(0.007)	(0.006)	(0.023)	(0.006)	(0.006)	(0.023)	(0.006)	(0.006)
Tenure in current firm squared	0.001	-0.000	-0.000	0.001	-0.000	-0.000	0.001	-0.000*	-0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Female	0.058	-0.028	-0.077*	0.154	-0.010	-0.072	0.117	0.003	-0.059
	(0.152)	(0.038)	(0.046)	(0.153)	(0.040)	(0.045)	(0.155)	(0.038)	(0.045)
Reading Score	-0.131***	-0.017	-0.009	-0.132***	-0.004	0.001	-0.130***	-0.002	-0.001
	(0.033)	(0.017)	(0.011)	(0.033)	(0.014)	(0.009)	(0.033)	(0.013)	(0.010)
Numeracy Score	-0.037	-0.012	-0.012	-0.032	-0.014	-0.009	-0.031	-0.014	-0.011
	(0.038)	(0.013)	(0.011)	(0.036)	(0.012)	(0.011)	(0.035)	(0.013)	(0.010)
Extraversion	0.013	0.026	0.015	-0.005	0.027	0.013	0.006	0.027	0.009
	(0.052)	(0.020)	(0.017)	(0.054)	(0.019)	(0.016)	(0.055)	(0.018)	(0.016)
Openness to Experience	-0.028	0.042**	0.016	-0.008	0.048**	0.014	-0.004	0.039*	0.007
	(0.060)	(0.022)	(0.016)	(0.059)	(0.020)	(0.015)	(0.060)	(0.020)	(0.014)
Conscientiousness	0.142**	0.030	0.018	0.116*	0.014	-0.003	0.116*	0.021	-0.001
	(0.069)	(0.020)	(0.018)	(0.065)	(0.019)	(0.017)	(0.064)	(0.018)	(0.016)
Emotional Stability	0.072	0.006	0.008	0.086	0.003	-0.001	0.095*	0.013	0.004
	(0.056)	(0.018)	(0.019)	(0.054)	(0.018)	(0.018)	(0.054)	(0.018)	(0.016)
Agreeableness	0.072	0.016	0.004	0.073	0.012	0.000	0.073	0.007	0.001
	(0.053)	(0.024)	(0.019)	(0.051)	(0.022)	(0.019)	(0.050)	(0.022)	(0.019)
Firm characteristics				YES	YES	YES	YES	YES	YES
Occupation dummies							YES	YES	YES
Mother has no formal education	0.332***			0.381***			0.386***		
	(0.105)			(0.106)			(0.105)		
Constant	2.304***	4.444***	3.085***	2.088***	3.936***	2.986***	1.791***	4.150***	3.225***
	(0.333)	(0.454)	(0.094)	(0.416)	(0.317)	(0.113)	(0.456)	(0.295)	(0.118)
m00		0.457***			0.355***			0.349***	
		(0.152)			(0.108)			(0.102)	
m11			0.260**			0.094			0.124
			(0.120)			(0.095)			(0.095)
Observations	3,576	1,821	1,755	3,576	1,821	1,755	3,576	1,821	1,755
R^2		0.428	0.369		0.443	0.383		0.479	0.420

Notes: Logit models with clustered standard errors are used in the first step. Standard errors in the second step are bootstrapped (500reps) and clustered.
*** p<0.01, ** p<0.05, * p<0.1