Cognitive and Non-Cognitive Skills Affect Employment Outcomes: Evidence from Central Asia

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Abstract

Using a novel survey on cognitive and non-cognitive skills in Tajikistan and Uzbekistan, we analyse the relationship between skills and labour market outcomes. We find a strong link between employability and cognitive and non-cognitive skills. Skills further influence the type of employment, namely whether people are employed in 'new economy' occupations, i.e. jobs that require above average above average non-routine cognitive/analytical skills and above average non-routine interpersonal skills, the private sector and the so-called 'modern' sector. We also find robust and positive association between skills and job satisfaction. Finally, we find evidence that skilled individuals are more likely to pursue high levels of educational attainment, suggesting that there is an indirect link between skills and labour market outcomes, with skills being acquired in the process of formal education. Finally, we find evidence that skills are associated with higher wage rates, and hence, labour productivity.

JEL Classification C31, J24, I24

Key words: returns to cognitive skills, returns to non-cognitive skills, employment outcomes

1. Introduction

Central Asia is a diverse region consisting of low-income (Kyrgyz Republic and Tajikistan) and upper-middle-income (Kazakhstan, Turkmenistan, and Uzbekistan) countries. The transition process from central planning to the market system has been unfolding at a slower pace compared to other Eastern European countries (EBRD Transition Report 2013; Arias, et al, 2014). Economic growth in the region has been due in large part to natural resources, especially in the upper-middle income countries. All of the countries in Central Asia are attempting to diversify their economies towards the manufacturing and services industries, and to do so they realize that human capital is vital to their diversification strategies (Gill, et al. 2014).

The main objective of this paper is to study the link between skills, employability and productivity of workers. The paper, therefore, goes beyond a majority of studies, which generally investigate the impact of educational attainment on employment outcomes and productivity by specifically separating out skills from educational attainment. The study uses data from two Central Asian republics, namely Uzbekistan and Tajikistan and relies on novel surveys conducted jointly by the World Bank and German Society for International Cooperation (GIZ) in 2013. The surveys which contained modules typical of most labor force surveys, also contained modules that assessed the respondent's cognitive (memory, literacy and numeracy) and non-cognitive skills (openness, workplace attitude, decision making, achievement striving and mind set factor).

The paper makes three key contributions to the literature. First, we estimate the likelihood of employment of working age people in Tajikistan and Uzbekistan to understand the impact of the cognitive and non-cognitive skills distribution on employment. Analysing the impact of skills on employment is a relatively nascent area of work, but quantitative work in countries that have not undergone significant market reforms is completely absent. In doing so, we take particular precautions to ensure that the impact of skills on educational attainment is captured. Second, we explore the link between cognitive and non-cognitive skills on the type of employment - namely, employment in the so-called 'new economy' jobs[1], modern sector jobs[2], private sector, and public sector. To our knowledge, no other study has linked skills with the type of employment. Third, we analyse the link between wages, and hence, productivity, and cognitive and non-cognitive skills. Again, this type of analysis has not been conducted in a country that is embarking on market based reforms.

The key findings that emerge from the paper are as follows. First, we find that better skilled people are more likely to be employed. More specifically, we find that better skilled people are more likely to be employed in new economy jobs, in the modern sector and in the private sector. Second, we find that better skilled workers have higher job satisfaction. Third, we find that cognitive and non-cognitive skills impact labour market outcomes indirectly, i.e. through the signal that education attainment (diplomas) has on hiring decisions, and not directly. In addition, we posit a second channel through which skills impact upon education attainment – in line with some of the previous research, we argue that education attainment is, in part, determined by level

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[1] We define 'new economy' jobs to be jobs requiring: (a) above average non-routine cognitive/analytical skills; and/or (b) above average non-routine interpersonal skills.

[2] We define 'modern sector' as a Kuznets-like combination between industry and services.

of skills that a person possesses. Finally, we find that workers with higher cognitive and non-cognitive skills have higher wages, and hence are likely more productive.

This paper is organised as follows. Section 2 provides a summary of the related literature, whilst section 3 presents details of the data, sampling methodology and basic descriptive statistics of the variables used in this study. Section 5 presents an overview of the results and the robustness checks that are employed in the study. Section 6 presents the results and concludes.

2. Literature review

Past work has shown a strong and robust relationship between cognitive skills and labour market outcomes. Studies using longitudinal household surveys in the US find that cognitive test scores during schooling years are good predictors of the level of wages (Heckman (2000), Heckman and Carneiro (2003), Cunha, Heckman, Lochner and Masterov (2006), Roberts et al (2007)). Moreover, the empirical evidence shows that shortage of skills is considered to be one of the biggest barriers to employment (Sanchez Puerto (2009)). The empirical literature on the cognitive skills/labour market outcomes distils two types of causal pathways: (i) direct - e.g. Murnane, Willett and Levy (1995) assess the role of math skills of graduating high school seniors on their wages at age 24 and found a positive and increasing impact of cognitive skills on wages; and (ii) indirect - e.g. Cunha et al (2005) argue that cognitive skills increase the likelihood of acquiring higher level of education, which in turn leads to higher economic returns.

Similar findings are suggested by a summary of the literature on the cognitive skills/labour market outcomes nexus provided by Tyler (2004). This literature suggests a substantial premium for cognitive skill in the US labour market at least (Howell and Wolff, 1991; Murnane et al., 1995; Murnane et al., 2000; Bowles et al., 2001). Moreover, a number of key studies have suggested that the return to cognitive skills has increased over time (Howell and Wolff, 1991; Murnane et al., 1995), although the evidence on this point is not necessarily conclusive (Bowles et al., 2001). Furthermore, cognitive skills play a more important part in determining earnings for some groups of students. For example, Tyler (2004) suggested a substantial labour market value for basic cognitive skills particularly for young people who have dropped out of high school and who are early on in their careers. Blackburn and Neumark (1993) also found a higher return to graduating from college for those with higher levels of cognitive skill, although this was not by and large supported by Murnane and Willet (2004).

Going down to more specific cognitive skills, key papers by McIntosh and Vignoles (2001) and Dearden et al. (2002) showed, using UK data from the 1990s, that numeracy and literacy skills have a strong association with individuals' labour market outcomes. The results from these papers were derived from two data sources. The first is a data set that contains information on a cohort of individuals born in 1958 (the National Child Development Study). Individuals in this data set were assessed in terms of their literacy and numeracy in 1995. These data were limited by the fact that only 10% of the NCDS sample undertook literacy and numeracy tests and sample sizes are therefore extremely small. The second source is the International Adult Literacy Survey, which surveyed the literacy and numeracy skills of a cross section of individuals aged 16–64 in 1996. This latter data set is limited by the fact that it is not particularly rich, in terms of family background variables. Acknowledging the caveats about the data, Dearden et al. (2002) found a large positive effect on earnings and employment rates from having better numeracy skills. Other studies, namely McIntosh and Vignoles (2001) on the same data sets, and more recently Grinyer (2005) with cross section data, confirm the positive relationship between better literacy and numeracy and earnings and employment rates.

Similarly, there is growing evidence that non-cognitive skills are as important for labour market outcomes. Even though a more recent phenomenon, the empirical literature on the skills/labour market outcomes nexus finds a strong and robust relationship between certain non-cognitive skills, such as dependability, persistence and docility and labour market outcomes (Heckman et al (2006), Bloom and Saeki (2010) and Heckman and Cunha (2010)). A separate strand of the literature has argued that non-cognitive skills are particularly valued in certain sectors (e.g. services). Finally, recent evidence in the context of high-income countries has suggested that employers value non-cognitive abilities more than cognitive ability or independent thought (e.g. Bowles et al (2001).

A special strand of the literature has focused on studying the link between skills/competencies and labour market outcomes in a more advanced age, mainly stemming from and building on the data gathered through PIAAC (Programme for International Assessment of Adult competencies), which addressed the concerns of skills diminishing over age (for a full discussion, please refer to Desjardin and Warnke (2012)). The additions of this strand of the literature are numerous, from papers that have looked at the link between numeracy and literacy on one hand (as well as investments in education) and income inequality on the other (Solga (2014)), to returns on labour as age advances and skills commence to decay (Desjardin and Warnke (2012)). Finally, this strand of the literature has also tapped into an important facet of modern day markets – the skills/job satisfaction nexus (Allen and Van der Velden, 2001, Allen, Levels and Van der Velden, 2013).

3. Data and Methodology

This study uses two unique household surveys conducted jointly by the World Bank and the German Society for International Cooperation (GIZ) in Tajikistan and Uzbekistan. Both surveys were carried out in 2013. The surveys are nearly identical in design and are both representative at the national, and urban and rural levels. Two distinct instruments are employed in the survey: a core questionnaire, which is typical of most labour force surveys, and a skills questionnaire. Qualitative testing and pilots helped fine-tune the questionnaires and organize the modules in order to administer the survey efficiently and consistently.

The Tajik sample size of the core questionnaire is 3,300 households with a total of 20,142 individuals. One or two individuals per household were randomly selected to participate in the skills module of the overall survey questionnaire. The second skills questionnaire sample consists of 4,892 individuals.

The Uzbek sample size of the core questionnaire is 1,500 households with a total of 8,622 individuals. The second skills questionnaire sample thus consists of 1,500 individuals.

1. Core questionnaire

The core questionnaire contains modules focusing on: education, employment, migration, health expenditure, remittances, government transfers, financial services, subjective poverty, housing conditions, and household expenditures. The core questionnaire concludes with the random selection of a household member aged 15 to 64 who is not a current migrant (the selection is based on a random number table or Kish grid) to be the subject for the skills questionnaire.

2. Skills questionnaire

The skills questionnaire contains detailed modules on labour and work expectations, migration and preparation for migration, language skills, and technical skill training. A unique aspect of the survey is the battery of cognitive and non-cognitive questions, which helps to test a respondent's ability. The non-cognitive test modules of the skills questionnaire are based on World Bank Skills Toward Employment and Productivity (STEP) surveys. The skills modules were developed with the support of a multi-disciplinary panel of experts in psychology, skills assessment, education, and labour markets.

Cognitive skills

Data for this study come from a 34-item survey module designed for use by the World Bank to assess five different "cognitive" skills. These cognitive skills can be conceptualized as falling into two domains: (i) Executive functioning skills, defined as the cognitive control capacities that enable individuals to "organize their thinking and behaviour with flexibility, decrease their reactive responding to contextual cues and contingencies, and engage in self-regulated … behaviour" (Welsh et al., 2010); (ii) Domain-specific skills, consisting of "knowledge of ideas, facts and definitions, as well as … formulas and rules" (Boekarts, 1997, p. 164) about specific domains such as literacy and numeracy. In turn, each broader domain can be conceptualized as including other branches; mathematics, for example, includes concepts such as number recognition, arithmetic, and graph comprehension (Fuchs et al., 2005; Pinker, 1990).

These domains are not meant to be exhaustive, but to serve as useful heuristics. Moreover, executive functioning skills and domain-specific skills are related: A number of recent studies provide evidence that executive functioning skills such as working memory actually contribute to the development of literacy and numeracy skills (Blair & Razza, 2010; Swanson, Jerman, & Zheng. 2008). From a policy perspective, this suggests that educators should focus on the promotion of both executive functioning and domain-specific skills, particularly in the pre-school and elementary school years when such functions are most malleable to intervention (Welsh et al., 2010).

Using item factor analysis, the researchers created three basic cognitive skills: Memory, Literacy and Numeracy. A more detailed description of the item factor analysis as well as how various questions were distilled into the three cognitive scores above is provided in the annex of the paper. .

Non-cognitive skills

Data for this study come from a 33-item survey module designed for use by the World Bank to assess 11 different "non-cognitive" skills (see Table 1, below; Duckworth & Guerra, 2012).

These non-cognitive skills can be conceptualized as falling into two domains: (i) Personality traits, defined as enduring patterns of thinking, feeling, and behaving which are relatively stable across time and situations (Borghans, Duckworth, Heckman, & ter Weel, 2008; Paunonen, 2003). The "Big Five" factors of personality – openness, conscientiousness, extraversion, agreeableness, and neuroticism (or emotional stability) – are the most widely accepted taxonomy of broad personality traits (Goldberg, 1990), having been validated for use across developmental stages (John & Srivastava, 1999) and cultures (Soto, John, Gosling, & Potter, 2008). (ii) Socio-emotional skills, defined as the learned knowledge, attitudes and skills necessary to understand and manage emotions, set and achieve positive goals, establish and maintain positive relationships, and make responsible decisions (CASEL, 2014).

Similarly to the cognitive skills scenario above, here as well, an item factor analysis was used in order to create the five types of non-cognitive (socio-emotional) skills: (i) extraversion; (ii) workplace attitudes and behaviours; (iii) decision making; (iv) achievement striving; (v) fixed versus growth mind set. Further explanation of how these measures were constructed (along with additional issues connected with the item factor analysis) is provided in the annex of the paper. .

Table 1 below provides summary of the basic descriptive statistics per skill/measure on a country-by-country basis.

Table 1: Summary of basic statistics

	Observations	Mean	Std. Dev	Min	Max
Uzbekistan					
Monthly salary	2155	5.957442	0.755248	2.995732	9.904487
Memory skills	1500	-0.02967	0.826215	-2.135	2.469
Literacy Skills	1500	0.024399	0.709931	-1.946	1.476
Numeracy skills	1500	0.179585	0.717593	-2.113	1.806
Openness	1500	0.548105	0.813504	-2.093	2.202
Workplace attitude	1500	0.782211	0.785276	-2.579	2.108
Decision making	1500	0.130443	0.77318	-2.405	2.31
Achievement striving	1500	0.538138	0.831152	-2.089	2.138
Mind set factor	1500	0.099179	0.839762	-2.467	2.678
Tajikistan					
Monthly salary	4287	6.389695	0.935886	2.302585	10.81978
Memory skills	4862	-0.01737	0.924302	-2.135	2.469
Literacy skills	4862	-0.03886	0.787801	-1.946	1.476
Numeracy skills	4862	-0.08727	0.862049	-2.113	1.806
Openness	4821	-0.15921	0.750693	-3.183	2.115
Workplace attitude	4821	-0.25908	0.780549	-3.401	2.108
Decision making	4821	-0.19075	0.718102	-2.524	2.241
Achievement striving	4821	-0.19475	0.777842	-3.261	2.138
Mind set factor	4862	-0.00973	0.890048	-2.467	2.678

In doing our analysis we follow a two-pronged approach. First, we model the association with possibility of being employed (a probit analysis); second, in analysing the association of skills with productivity, we follow an adaptation of the basic Mincer (1974) model whereby we regress the log of wages on skills, education attainment and a battery of control variables (individual characteristics, including genders, residence and age).

There are a few caveats in this research however. Even though we try to control for omitted variable bias, the questionnaire is conducted in a way that does not always allows for it. Previous literature suggests a number of key candidates for omitted variable bias, the most significant being ability bias (Griliches, 1977). It may be that some of the apparent role of skills in influencing earnings is actually due to the fact that more able individuals (who would earn more anyway) also have better basic skills. Previous models (Vignoles et al, 2011) have included test scores from cognitive skill tests undertaken at age five and ten. The age five tests in particular, not being based specifically on reading or number skill, should proxy an individual's ability rather than simply measuring their literacy or numeracy or indeed the effects of their schooling. However, in this particular survey, both the skills (cognitive and non-cognitive) and wages/employability are both measured in the same time, hence increasing the potential omitted variable problem.

The existing literature also highlights the importance of family background and parental attitudes and motivations in determining individuals' cognitive skill levels (Todd and Wolpin, 2003). To address this particular potential source of omitted variable bias, some past research have included a range of individual and family characteristics that have been found to significantly affect educational achievement, and may also proxy unobserved family factors that influence both literacy and numeracy and subsequent earnings. However, the survey does not include any questions on this matter and hence controlling for them is impossible.

Perhaps the most significant limitation of our data is that information on individuals' skills is contemporaneous to measures of their earnings, unlike for example some previous US work on this issue by Murnane et al. (1995). It is possible that the causal link runs in the opposite direction to the one we might expect: individuals who secure high quality jobs with high earnings may tend to improve or maintain their basic skills. By contrast individuals in low quality jobs with lower earnings may find that their skills diminish over time. Yet at the same time if individuals have changing levels of basic skills over their working life, this is also good reason to focus on the value of their current skill levels. Hence, it is important to treat our final results as an association between skills set and earnings/employability (as determining causality from a one-off cross-section sample pauses further methodological challenges).

The final limitation to our findings relates to the size of the sample. It is important to stress that less than a half of the sample responded to questions relating to their wages, which, significantly limits our analysis as well as the prospect of generalizing our results. The sample that responded to the wage questions and the entire sample reveal that the workers in the two samples are statistically identical for the set of observed variables. However, we remain uncertain that the sample of workers who respondents who answered the wage modules might be correlated with unobservables.

4. Results

Table 2 and 3 summarize the main findings from the impact of skills on employment. Holding other included individual characteristics constant, cognitive and non-cognitive skills significantly affect employment outcomes. In conducting this exercise we proceed as follows- first we regress only employment and cognitive skills (while also including individual characteristics) (model 1).

We then repeat model 1 but only using non-cognitive skills (model 2). Model 3 includes both cognitive and non-cognitive skills. Finally, models 4-6 repeat the same analysis whilst also adding dummy variables that capture education attainment. The significance and magnitude of the coefficients of the skills variables in the education outcome regression decreases once the education attainment dummy variables are introduced. In both Tajikistan and Uzbekistan, the skills variables lose significance when the education attainment dummy variables are introduced because there is a correlation between educational attainment and skills. Overall, the results suggest that in Tajikistan, numeracy and decision making, and to some extent memory, are positive and significant determinants of employment. In Uzbekistan, memory and decision making, and to a lesser extent workplace attitude, are positive and significant determinants of employment.

Table 2. Tajikistan: Probit analysis of employment and skills

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	0.0566*		0.0507	0.00345		-0.000874
	(0.0310)		(0.0312)	(0.0322)		(0.0324)
Literacy	-0.0631		-0.0914	-0.111		-0.130
	(0.0519)		(0.0527)	(0.0530)		(0.0537)
Numeracy	0.206***		0.224***	0.167***		0.184***
	(0.0483)		(0.0488)	(0.0492)		(0.0497)
Openness		-0.0161	-0.0434		-0.0552	-0.0650
		(0.0465)	(0.0469)		(0.0473)	(0.0476)
Workplace attitude		0.0884	0.0853		0.0447	0.0478
		(0.0571)	(0.0571)		(0.0580)	(0.0579)
Decision making		0.123***	0.131***		0.106***	0.110***
		(0.0334)	(0.0334)		(0.0338)	(0.0337)
Achievement striving		0.0367	0.0269		0.0571	0.0565
		(0.0600)	(0.0599)		(0.0608)	(0.0606)
Mindset factor		0.0247	0.0537**		0.0275	0.0419
		(0.0266)	(0.0271)		(0.0272)	(0.0275)
Secondary				0.240***	0.236***	0.225***
				(0.0597)	(0.0595)	(0.0601)
Secondary specialised				0.846***	0.861***	0.832***
				(0.0905)	(0.0889)	(0.0905)
Tertiary				1.176***	1.166***	1.129***
				(0.0929)	(0.0908)	(0.0939)
N	4862	4821	4821	4862	4821	4821

The equations also control for age, gender and the rural/urban divide
Standard errors in parentheses
="* p<0.1 ** p<0.05 *** p<0.01"

Table 3. Uzbekistan: Probit analysis of employment and skills

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	0.163***		0.156***	0.125**		0.118**
	(0.0510)		(0.0523)	(0.0521)		(0.0533)
Literacy	0.00125		0.0276	-0.0129		0.0120
	(0.0771)		(0.0783)	(0.0790)		(0.0800)
Numeracy	0.0338		-0.00388	0.0196		-0.0135
	(0.0785)		(0.0797)	(0.0819)		(0.0833)
Openness		0.0644	0.0380		0.0786	0.0595
		(0.0646)	(0.0652)		(0.0662)	(0.0667)
Workplace attitude		0.145*	0.122		0.0940	0.0828
		(0.0768)	(0.0773)		(0.0773)	(0.0776)
Decision making		0.160***	0.165***		0.135***	0.139***
		(0.0506)	(0.0511)		(0.0523)	(0.0525)
Achievement striving		-0.114	-0.108		-0.0906	-0.0888
		(0.0787)	(0.0792)		(0.0815)	(0.0817)
Mindset factor		-0.0630	-0.0661		-0.0698	-0.0714*
		(0.0420)	(0.0420)		(0.0425)	(0.0426)
Secondary				0.699***	0.687***	0.688***
				(0.134)	(0.134)	(0.135)
Secondary specialised				0.935***	0.938***	0.923***
				(0.129)	(0.129)	(0.130)
Tertiary				1.353***	1.380***	1.336***
				(0.165)	(0.165)	(0.166)
N	1500	1500	1500	1500	1500	1500

The equations also control for age, gender and the rural/urban divide.
Standard errors in parentheses
="* p<0.1 ** p<0.05 *** p<0.01"

Our results from the tables above fit with the overall literature on the skills and labour market outcomes. First, we found that certain cognitive and non-cognitive skills are associated with higher probability of being employed. Previously, in the context of Canada, Charette and Meng (1998) find that higher numeracy skills enhance the probability of being employed. Similarly to our findings on the skills/probability of being employed nexus, they do not find any statistically significant link between literacy skills and the probability of being employed. Similarly, Rivera Batiz (1992) reports similar findings for the impact of a numeracy variable on fulltime employment. Our second most important finding suggests that the magnitude and significance of the skills variables decrease, once education attainment variables are added to analysis. Findings of similar nature are reported in a paper that studies the important of education/skills on labour market outcomes in the Netherlands (van der Welden and Wolbders (2007). The importance of education as a variable that explains most of the variation of labour market outcome could be found elsewhere (van der Werhofst (2011), for instance, relying on cross-national dataset of 18 countries, finds a much stronger and more robust link between education attainment and labour market outcomes, suggesting that educational qualifications provide a lot of information about the skills that students acquired).

In that respect, our findings are compatible with both, the signalling theory (Spence 1974) and credential theory (Collins, 1979).The signalling theory acknowledges that educational attainment and cognitive skill may not be perfectly correlated, but it argues that employers have only limited information about employees' actual skills. So, even though employers seek to reward skill, they must use educational attainment as an index of skill. Thus, it is likely that occupational rewards reflect workers' educational attainments more than their actual skills, especially during the early period of their employment with a particular employer. On the other hand, the credential theory views educational attainment as a biased indicator of skill that is used by the powerful groups in the society to filter out equally talented but uncertified workers. Hence, it considers educational credentials to be a much more important determiner of labour force rewards and participation than is skill. But credential theory sees this imbalance as the result of discrimination, whereas signalling theory sees it as the result of limited information.

However, we do not exclude the possibility of skills to have an impact on employment and we posit another channel though which skills impact upon the probability of being employed. Namely, we argue that people with higher skills (both cognitive and non-cognitive) would also tend to be more educated, thus (following some of the theories enumerated above) increasing their probability of being employed. In that respect, table 4 below succinctly summarizes the initial results of our analysis[34]. Our findings are consistent with Heckman, Stixrud, Urza (2006), who show that cognitive and noncognitive skills influence employment, especially through schooling decisions. In simulation exercises, however, Heckman et al (2006) shows a somewhat higher gradient for non-cogntive compared to cognitive skills.

[3] Note, the best way to show the impact of skills on education (and ultimately on employment) would be to two a two-stage probit whereby the first stage would regress education attainment on skills and individual characteristics, whilst the second stage would use the instrumented education variable from the first stage equation, the skills variable and the additional controls. In a way, table 4 above only shows the results from the first stage regression analysis.

[4] Note: there are a couple of caveats attached to this approach, which mainly stem from the nature of the data used. First, both cognitive and non-cognitive skills are assessed contemporaneously. For the best instrumentation, one should assume that skills in period t-1 would have an impact on education outcomes in period t. Second and probably most importantly, family background (i.e. maternal and paternal education) is considered to have a particular impact on the level of educational attainment. Thirds, there is a significant reverse causality between the two variables (skills and educational attainment) as pointed by the existing literature (Lleras (2008), Duckworth and Schoon (2010), Hanushek and Woessmann (2009)). As pointed above, given the nature of our dataset and the lack of family background data, we are unable to control for these variables.

Table 4. OLS results of education on skills

	Tajikistan	Uzbekistan
Memory	0.139***	0.116***
	(0.0187)	(0.0325)
Literacy	0.0812***	0.0487
	(0.0289)	(0.0515)
Numeracy	0.114***	0.0377
	(0.0278)	(0.0531)
Openness	0.0530*	-0.0273
	(0.0283)	(0.0437)
Workplace attitude	0.0996***	0.0972*
	(0.0329)	(0.0510)
Decision making	0.0710***	0.0767**
	(0.0196)	(0.0337)
Achievement striving	-0.0666*	-0.0499
	(0.0354)	(0.0514)
Mindset factor	0.0405***	0.0160
	(0.0145)	(0.0272)
N	4821	1500
R-sq	0.210	0.099
adj. R-sq	0.208	0.092

Standard errors in parentheses

="* p<0.1 ** p<0.05 ** p<0.05

The dependent variable is a categorical variable assuming values from 0-3, depending on the level of education completed. In addition, the regression analysis controls for: age, gender, locality (rural/urban divide), family welfare (per capita consumption) and family size.

Skills however, do not equally matter for different jobs. As the economies develop and prosper, they also undergo a process of structural shift, whereby jobs are shifted from the traditional sectors (agriculture and mining) to the modern ones (industry and agriculture). This shift also implies a rise in importance of the cognitive and non-cognitive skills in the so-called 'modern' sector (OECD, 2010). In order to gauge some of the subtleties of the skills/employment nexus, especially as economies further develop and prosper, we repeat the probit analysis from above whilst restricting the samples on males and females, separately, as well as whilst paying special attention to the employment in the new economy sector, the private sector, the so-called 'modern' sector (industry and services) as well as the public sector. The results of this exercise are reported in Tables 5 (Tajikistan) and 6 (Uzbekistan).

Table 5. Tajikistan: Probit analysis of employment and skills - subsectoral analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	-0.0389	0.0223	0.109***	-0.0400	-0.000874	0.0583*
	(0.0517)	(0.0415)	(0.0389)	(0.0342)	(0.0324)	(0.0351)
Literacy	-0.0850	-0.165**	0.0165	-0.0902	0.130**	-0.0804
	(0.0880)	(0.0682)	(0.0626)	(0.0572)	(0.0537)	(0.0596)
Numeracy	0.141*	0.206***	0.0873	0.0904*	0.184***	0.163***
	(0.0832)	(0.0623)	(0.0589)	(0.0527)	(0.0497)	(0.0559)
Openness	-0.0912	-0.0366	0.0128	0.127***	-0.0650	0.0323
	(0.0755)	(0.0611)	(0.0559)	(0.0489)	(0.0476)	(0.0538)
Workplace attitude	0.0764	0.0385	0.0395	0.0564	0.0478	0.0144
	(0.0925)	(0.0738)	(0.0685)	(0.0615)	(0.0579)	(0.0647)
Decision making	0.199***	0.0485	0.0337	0.0434	0.110***	0.0787**
	(0.0581)	(0.0413)	(0.0398)	(0.0364)	(0.0337)	(0.0361)
Achievement striving	0.00380	0.0746	0.0195	0.0469	0.0565	0.0112
	(0.0994)	(0.0769)	(0.0716)	(0.0646)	(0.0606)	(0.0683)
Mindset factor	0.0273	0.0468	0.0692**	0.0399	0.0419	0.0152
	(0.0446)	(0.0351)	(0.0338)	(0.0290)	(0.0275)	(0.0314)
N	1741	3080	4821	4821	4821	4821

The equations also control for age, gender and the rural/urban divide

Standard errors in parentheses

="* p<0.1 ** p<0.05 *** p<0.01"

Table 6. Uzbekistan: Probit analysis of employment and skills: sub-sectoral analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	0.0368	0.156**	0.165***	-0.00429	0.118**	0.162***
	(0.0936)	(0.0647)	(0.0605)	(0.0559)	(0.0533)	(0.0544)
Literacy	0.115	-0.0526	-0.0495	0.124	0.0120	-0.0758
	(0.141)	(0.0973)	(0.0870)	(0.0932)	(0.0800)	(0.0815)
Numeracy	-0.0877	0.00908	-0.0378	-0.0813	-0.0135	0.0329
	(0.152)	(0.0982)	(0.0928)	(0.0957)	(0.0833)	(0.0876)
Openness	-0.189	0.201**	0.00750	0.0282	0.0595	0.0108
	(0.125)	(0.0807)	(0.0776)	(0.0777)	(0.0667)	(0.0694)
Workplace attitude	0.314**	-0.00170	0.0157	-0.0372	0.0828	0.147*
	(0.144)	(0.0929)	(0.0913)	(0.0866)	(0.0776)	(0.0823)
Decision making	0.200**	0.106*	0.109*	0.0749	0.139***	0.110**
	(0.0987)	(0.0629)	(0.0560)	(0.0622)	(0.0525)	(0.0521)
Achievement striving	-0.138	-0.0934	0.186**	-0.0671	-0.0888	-0.0756
	(0.157)	(0.0966)	(0.0912)	(0.0957)	(0.0817)	(0.0817)
Mindset factor	-0.182**	-0.0169	0.0240	-0.107**	-0.0714*	0.0213
	(0.0823)	(0.0506)	(0.0473)	(0.0482)	(0.0426)	(0.0430)
N	488	1012	1500	1500	1500	1500

The equations also control for age, gender and the rural/urban divide

Standard errors in parentheses

="* p<0.1 ** p<0.05 *** p<0.01"

In the case of Tajikistan, cognitive skills and non-cognitive skills are positively associated with the type of employment. Memory and mindset factor are positively correlated with the probability of being employed in the 'new economy' sector, numeracy and openness with the probability of being employed in the private sector, numeracy and decision making with probability of being employed in the modern sector, as well as numeracy and decision making with the probability of being employed in the public sector.

In Uzbekistan, too, cognitive and non-cognitive skills are associated with the type of employment. More specifically: (i) memory, decision making and achievement striving are positively correlated with the probability of being employed in the new economy sector; (ii) memory and decision making are positively correlated with the probability of being employed in the modern sector; (iii) memory, workplace attitude and decision making are positively correlated with the probability of being employed in the public sector.

In both Tajikistan and Uzbekistan, the strong correlation between educational attainment and skills and the sector of employment is consistent with the above findings. In order to gauge this relationship (i.e the strong correlation between skills and education attainment per sector) we conduct a simple exercise, whereby we try to see if there is an overlap in the sectors who: (i) hire workers with higher skillset; (ii) hire most of the employees with tertiary degrees[5]. We find that people with stronger cognitive and non-cognitive skills are generally more educated and tend to be attracted to a certain higher value added, well paid and status driven sectors. In Tajikistan, three sectors in particular: mining, finance and international organizations (embassies and the UN) tend to hire most of the employees who scored extremely well on the cognitive skills test and have high education attainment (have a tertiary degree or higher)[6]. Similarly, in Uzbekistan, public administration and education are the sectors where most of the high education attainment and highly skilled people are employed[7].

Building on the literature on the link between skills and job satisfaction, our final analysis involves analysing the skills/job satisfaction nexus. The results of this analysis are presented in Table 7. We find a robust link between certain cognitive and non-cognitive skills and job satisfaction. In Tajikistan, numeracy and decision making (and to certain extent mindset factor) are associated with a higher probability of being satisfied with one's job in the case of Tajikistan. Similar findings emerge in the case of Uzbekistan (though in this case only memory appears positive and significant).

[5] The sectors that we consider are: agriculture and fishing, mining, manufacturing, energy and water, construction, trade and repair, hotels and restaurants, transport and communication, finance, real estate, public administration, education, health and social work, utilities/social/personal services, private households with employed people, extra-territorial organizations (embassies, UN)

[6] The results are not as clear cut when non-cognitive skills are taken into consideration, although it appears that education, international organizations and trade are the sectors where most of the well educated/high non-cognitive skills people tend to be.

[7] The picture is similar vis-à-vis the non-cognitive skills.

Table 7. Skills and job satisfaction - probit analysis

	Tajikistan	Uzbekistan
Memory	-0.0498	0.210***
	(0.0331)	(0.0542)
Literacy	-0.0199	0.100
	(0.0564)	(0.0808)
Numeracy	0.206***	-0.0586
	(0.0513)	(0.0848)
Openness	-0.00318	0.0903
	(0.0489)	(0.0672)
Workplace attitude	0.0504	0.00166
	(0.0601)	(0.0800)
Decision making	0.134***	0.0537
	(0.0347)	(0.0542)
Achievement striving	-0.00613	0.00467
	(0.0632)	(0.0815)
Mindset factor	0.0518*	-0.0123
	(0.0286)	(0.0429)
N	4821	1500

The equations also control for age, gender and the rural/urban divide
Standard errors in parentheses
="* p<0.1 ** p<0.05 ** p<0.05

Tables 8 and 9 summarize the results of the Mincer equation of log on wages and skills for Tajikistan and Uzbekistan respectively. The following results are noteworthy. First, cognitive skills explain wages more than non-cognitive skills. Indeed, in the case of Tajikistan, memory is positive and significant (albeit at 10 per cent level of significance), whilst in the case of Uzbekistan, numeracy is positive and significant (at 5 per cent level of significance). Second, the significance of the skills coefficients do not hold once education attainment dummy variables are introduced. In the case of Tajikistan, the memory variable loses its significance, whilst in the case of Uzbekistan, the numeracy variable decreases in magnitude. Third, education attainment dummy variables are robustly significant and with the magnitude of coefficients increasing with the level of education attained. Carrying out the analysis separately for males and females produces similar patterns. The results from this robustness check are consistent with our overall findings and are available upon request. These findings feed into the existing literature of the importance of skills on labour productivity (e.g. Grogger and Eide (1995)). Some of the extant research suggests that mathematical skills have become an important predictor of wages, especially in the US context (Murnane et al (1995)). Our findings are also in line with recent research on skills/wage nexus (Heckman, Stixrud, Urza (2006)) who emphasize that (albeit in the US context) cognitive skills explain much of the variance of (log) wages. That is not to say that noncognitive skills are completely mute. Indeed, Osborne-Groves (2004) studies the effect of personality and behavioural traits on the wages of females. Using two data sets and alternative instruments for adult personality measures, she finds that personality traits such as fatalism, aggression, and withdrawal have significantly negative effects on wages.

Table 8. Tajikistan - OLS of log of wages and skills

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	0.0695*		0.0696*	0.0224		0.0232
	(0.0371)		(0.0375)	(0.0368)		(0.0372)
Literacy	0.0300		0.0113	-0.00553		-0.0181
	(0.0616)		(0.0618)	(0.0600)		(0.0603)
Numeracy	0.00495		-0.00197	-0.0107		-0.0189
	(0.0592)		(0.0593)	(0.0575)		(0.0580)
Openness		0.00169	-0.00967		-0.0396	-0.0388
		(0.0536)	(0.0535)		(0.0527)	(0.0525)
Workplace attitude		0.0742	0.0803		0.0468	0.0536
		(0.0619)	(0.0617)		(0.0591)	(0.0594)
Decision making		0.0447	0.0497		0.0222	0.0190
		(0.0442)	(0.0443)		(0.0431)	(0.0432)
Achievement striving		0.0367	0.0245		0.0600	0.0576
		(0.0672)	(0.0673)		(0.0648)	(0.0657)
Mindset factor		-0.0240	-0.0146		-0.0211	-0.0220
		(0.0335)	(0.0327)		(0.0313)	(0.0309)
Secondary education				0.227***	0.214**	0.216**
				(0.0870)	(0.0870)	(0.0869)
Secondary specialised				0.380***	0.358***	0.362***
				(0.102)	(0.103)	(0.104)
Tertiary				0.671***	0.639***	0.642***
				(0.0908)	(0.0893)	(0.0919)
N	1576	1565	1565	1576	1565	1565
R-sq	0.115	0.122	0.127	0.160	0.166	0.166
adj. R-sq	0.112	0.117	0.120	0.155	0.160	0.159

The equations also control for age, gender and the rural/urban divide.
Standard errors in parentheses
="* p<0.1 ** p<0.05 *** p<0.01"

Table 9. Uzbekistan: OLS of log wages on skills

	(1)	(2)	(3)	(4)	(5)	(6)
Memory	0.0182		0.0127	0.0185		0.0110
	(0.0417)		(0.0423)	(0.0394)		(0.0400)
Literacy	-0.0193		-0.0255	-0.0169		-0.0260
	(0.0634)		(0.0640)	(0.0601)		(0.0614)
Numeracy	0.164**		0.161**	0.130**		0.126**
	(0.0658)		(0.0658)	(0.0637)		(0.0636)
Openness		0.0785	0.0568		0.116**	0.0969*
		(0.0558)	(0.0580)		(0.0525)	(0.0551)
Workplace attitude		0.0355	-0.00658		0.0257	-0.00524
		(0.0690)	(0.0701)		(0.0640)	(0.0666)
Decision making		-0.000355	0.00742		-0.00472	0.00131
		(0.0466)	(0.0461)		(0.0434)	(0.0435)
Achievement striving		-0.0303	0.00143		-0.0662	-0.0401
		(0.0782)	(0.0794)		(0.0737)	(0.0762)
Mindset factor		-0.0356	-0.0333		-0.0465	-0.0446
		(0.0414)	(0.0405)		(0.0399)	(0.0395)
Secondary				-0.103	-0.0888	-0.0957
				(0.142)	(0.146)	(0.142)
Secondary specialised				-0.0259	-0.00156	-0.0200
				(0.137)	(0.138)	(0.136)
Tertiary				0.362**	0.421***	0.384***
				(0.142)	(0.141)	(0.141)
N	454	454	454	454	454	454
R-sq	0.186	0.169	0.191	0.252	0.247	0.260
adj. R-sq	0.175	0.154	0.171	0.237	0.229	0.236

The equations also control for age, gender and the rural/urban divide.
Standard errors in parentheses
="* p<0.1 ** p<0.05 *** p<0.01"

5. Discussion and conclusions

This paper quantifies the impact of cognitive and non-cognitive skills on labour markets outcomes in Tajikistan and Uzbekistan. We find that skills matter for the labour market outcomes. Controlling for individual characteristics, cognitive and non-cognitive skills in both countries (albeit at a various degrees) explain employment and wage rates, and hence, productivity levels. This is more apparent when the analysis is restricted to jobs that fall within the so-called 'new economy'. When educational attainment is held constant, the significance and the magnitude of most of the skills variables decreases, thus implicitly suggesting that cognitive and non-cognitive skills in Tajikistan and Uzbekistan impact labour market outcomes through education attainment.

Past studies have shown that education attainment and cognitive ability are generally positively correlated. This correlation exists for two reasons. First, to the extent that ability is an innate characteristic of an individual, it can influence school choice, since more abled people face lower costs to acquire education (Cunha, Heckman, Lochner, and Masterov, 2005). For this reason, people with higher cognitive ability are able to progress through the education levels and hence, achieve higher levels of attainment. In addition, cognitive skills can be built in particular in early stages of the life cycle through education and training (Mincer, 1958; Cunha, 2005; Cunha and Heckman, 2006).

In both, Tajikistan and Uzbekistan, educational attainment is correlated with better cognitive skills. Ajwad et al (2014b) and Ajwad et al. (2014c) show that cognitive ability is positively correlated with educational attainment among both working age men and women in Tajikistan and Uzbekistan respectively. Individuals with less than secondary education attainment typically score below average on all cognitive tests, including memory, literacy, and numeracy. Meanwhile, individuals who completed higher education typically scored above average on all cognitive skill assessments. Note that educational attainment remains a significant determinant of these cognitive scores even after controlling for background characteristics such as geographic area, age, marital status, household consumption quintile, and employment status.

Non-cognitive skills are positively correlated with schooling in Tajikistan and Uzbekistan. However, there is also a large degree of variation in non-cognitive skills among individuals with the same level of educational attainment. Non-cognitive skills are not always better among higher educated individuals across the entire distribution. In fact, there are respondents with less than a secondary education who scored higher on the non-cognitive skills measured than respondents with a higher education. Hence, while non-cognitive skills and educational attainment are correlated on average, the development of non-cognitive skills in school seems to vary substantially (World Bank, 2014a; World Bank, 2014b). These findings suggest that there may be variation in the extent to which non-cognitive skills are taught in schools and the quality of such teaching. Although, admittedly, families and communities have a central role in the early development of non-cognitive skills in children, and such factors should not be discounted.

Finally, we find a strong and robust link between skills and job satisfaction in the case of Tajikistan and Uzbekistan. The theoretical justification that is normally given for this relationship is quite straight-forward: people with better skills obtained better (and well paid) jobs which, they tend to enjoy more (see e.g. Allen and Van der Velden, 2001).

Our findings also bear a significant policy weight. First, they suggest that skills (both, cognitive and non-cognitive) matter for labour market outcomes (employability, productivity, job satisfaction) hence targeting education policies towards improving the average level of skills is an important way forward. Our analysis also suggests that most of the skills (especially the cognitive) are acquired in the process of formal education and thus, further investment in the education systems of both Tajikistan and Uzbekistan could yield tremendous benefits as they are moving on their path of economic development. Finally, our nuanced analysis suggests that skills/employability nexus is particularly relevant for the modern, new economy and the private sector. Given that this is where most of the value added comes from, and given the importance of these sectors as locomotives of economic growth and development, further investment in the education systems and skills themselves would not only improve the labour market outcomes, but it will also give a further impetus to the process of economic development in the region.

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Annex 1 – Cognitive skills

Background and Measures
Data for this study come from a 34-item survey module designed for use by the World Bank to assess five different "cognitive" skills. These cognitive skills can be conceptualized as falling into two domains:

Executive functioning skills, defined as the cognitive control capacities that enable individuals to "organize their thinking and behavior with flexibility, decrease their reactive responding to contextual cues and contingencies, and engage in self-regulated … behavior" (Welsh et al., 2010). *Domain-specific skills,* consisting of "knowledge of ideas, facts and definitions, as well as … formulas and rules" (Boekarts, 1997, p. 164) about specific domains such as literacy and numeracy. These domains are not meant to be exhaustive, but to serve as useful heuristics. Moreover, executive functioning skills and domain-specific skills are related: A number of recent studies provide evidence that executive functioning skills such as working memory actually contribute to the development of literacy and numeracy skills (Blair & Razza, 2010; Swanson, Jerman, & Zheng. 2008).

Analysis Strategy
All missing values were recoded as incorrect answers, resulting in a set of 33 dichotomous or binary items.[8] In choosing how to score the items, we were motivated by a primary concern of reducing the measurement error in each score. That is, when we administer a survey measure or test, we want to ensure that the variability in scores is due to what we are trying to measure – in this study, executive functioning or domain-specific skills – as opposed to error or bias. Traditional or unrefined methods of scoring – such as summing the survey items – do not account for this measurement error, leading to bias in future regression analyses. Refined scoring methods that account for measurement error include the production of factor scores using factor analysis or item response theory (IRT) methods.

Results
The initial EFA indicated that a one-factor model did not provide a good fit to the data (χ^2 (324) = 8981.68, CFI: .888, RMSEA: .082, .081 < 95% CI < .084).[9] Thus we decided that it was not feasible to proceed with an IRT analysis due to the plausibility of violating the dimensionality assumption. In examining the factor loadings, we noted that the 12 items making up the original construct of working memory loaded cleanly onto one factor. This factor was left intact and removed from the exploratory analyses. We then chose a 2-factor solution to model associations between the remaining 15 items. This model provided a good fit to the data (χ^2 (76) = 1261.15, CFI=.951, RMSEA=.063, .060 < 95% CI < .066) while modeling the observed indicators parsimoniously.

A confirmatory factor analysis then confirmed the fit of a 3-factor model for all 27 items in which factors were allowed to correlate (χ^2 (321) = 3128.37, CFI=.981, RMSEA=.033, .032 <

[8] Ideally, we would be able to identify four, not two, sets of responses: answered correctly; answered incorrectly; not answered and didn't know; and not answered due to time constraints or motivation but known. While such codes were initially included in the survey instrument, issues with data processing rendered such codes unusable. We were thus forced to collapse the codes into a dichotomous response: correct or incorrect. The implications of this choice are discussed further in the Implications and Future Directions section.

[9] In assessing model goodness of fit, the following criteria are used: A RMSEA < .08 provides an acceptable fit to the data, while an RMSEA < .05 provides a good fit to the data; a CFI > .9 provides an acceptable fit to the data while a CFI > .95 provides a good fit to the data (Kline, 2011).

95% CI < .034).[10] The three identified factors described in Table 1, below, were: (1) Working Memory (12 items); (2) Reading Comprehension (5 items); and (3) Informational Numeracy (10 items). In addition, preliminary measurement equivalence analyses indicate that this same factor structure provides a good fit to the data in Uzbekistan, Kyrgyzstan, and Tajikistan (χ^2 (97c3) = 10531.15, CFI=.953, RMSEA=.061, .060 < 95% CI < .062).[11] Finally, given the high correlation between the literacy and informational numeracy items, initial analyses were also conducted to determine whether a higher-order "cognitive" factor may account for the covariation between factors (Cattell, 1978).[12] This model was uninterpretable due to factor loadings above 1.

Table 1. Unstandardized Results from Final CFA of Cognitive Skills Module

		Loading	SE
Working Memory			
1	Working Memory Item 1	0.974	0.009
2	Working Memory Item 2	0.985	0.006
3	Working Memory Item 3	0.987	0.005
4	Working Memory Item 4	0.962	0.004
5	Working Memory Item 5	0.926	0.006
6	Working Memory Item 6	0.904	0.006
7	Working Memory Item 7	0.862	0.006
8	Working Memory Item 8	0.866	0.006
9	Working Memory Item 9	0.816	0.008
10	Working Memory Item 10	0.795	0.011
11	Working Memory Item 11	0.861	0.012
12	Working Memory Item 12	0.9	0.013
Reading Comprehension			
13	Reading Comprehension Item 13	0.8	0.012
14	Reading Comprehension Item 14	0.748	0.011
15	Reading Comprehension Item 15	0.843	0.009
16	Reading Comprehension Item 16	0.734	0.009
17	Reading Comprehension Item 17	0.788	0.01
Informational Numeracy			
18	Information Comprehension Item 18	0.522	0.014
19	Information Comprehension Item 19	0.553	0.013
20	Information Comprehension Item 20	0.588	0.013
21	Information Comprehension Item 21	0.812	0.009
22	Arithmetic Item 22	0.574	0.013
23	Arithmetic Item 23	0.741	0.01
24	Arithmetic Item 24	0.591	0.013
25	Graph Comprehension Item 25	0.726	0.012
26	Graph Comprehension Item 26	0.832	0.009
27	Graph Comprehension Item 27	0.667	0.011

[10] Factor correlations in the CFA were: Working Memory-Literacy (*r*=.428, *p*<.001), Working Memory-Informational Numeracy (*r*=.480, *p*<.001), and Literacy-Informational Numeracy (*r*=.69, *p*<.001).

[11] Tests of measurement invariance seek to establish whether we are measuring the same construct in the same way across different groups. As of this writing, our preliminary analyses have established *configural invariance:* that the same factor structure (e.g., the same number of factors and the same pattern of loadings) exists in the samples from all three countries. Future analyses will examine other levels of invariance, establishment of which increases our certainty that observed differences between countries is attributable only to true differences in the variability of the scores.

[12] For over a century, researchers have been interested in defining and measuring an overall measure of cognitive ability, or "g" factor (Jensen, 1998; Heckman, Stixrud, & Urzua, 2006). It is beyond the scope of this paper to comment extensively on such research; however, as developmental psychologists with an interest in applying research to policy, we take the position that it is useful to identify and understand the *components* of cognitive ability to better design programs to support the development of such skills.

Annex 2 – Non-cognitive skills

Data for this study come from a 33-item survey module designed for use by the World Bank to assess 11 different "non-cognitive" skills (see Table 1, below; Duckworth & Guerra, 2012). These non-cognitive skills can be conceptualized as falling into two domains:
Personality traits, defined as enduring patterns of thinking, feeling, and behaving which are relatively stable across time and situations (Borghans, Duckworth, Heckman, & ter Weel, 2008; Paunonen, 2003). *Socio-emotional skills*, defined as the learned knowledge, attitudes and skills necessary to understand and manage emotions, set and achieve positive goals, establish and maintain positive relationships, and make responsible decisions (CASEL, 2014). These domains are not meant to be exhaustive, but to serve as useful heuristics. Moreover, personality traits and socio-emotional skills are related: individuals with certain personality traits may tend to employ certain socio-emotional skills (McAdams, 1995). For program and policy purposes, however, there is a key distinction between personality traits and socio-emotional skills: while personality traits are predictive of labor market outcomes, they are less amenable to direct change via intervention. Socio-emotional skills, however, have been shown to be malleable to various intervention efforts across cultures (e.g., Jones, Brown, Aber, 2011; Torrente et al., 2014). In turn, building socio-emotional skills can result in changes to enduring patterns of thinking and behaving (Dweck, 2008).

Table B1. Original 33 Items Included in the Non-Cognitive Skills Module[13]

Personality Traits	*Extraversion*	
		Are you talkative?
		Do you like to keep your opinions to yourself? Do you prefer to keep quiet when you have an opinion? (R)
		Are you outgoing and sociable, do you make friends easily?
	Conscientiousness	
		When you perform a task, are you very careful?
		Do you prefer relaxation more than hard work? (R)
		Do you work very well and quickly?
	Openness	
		Do you come up with ideas others haven't thought of before?
		Are you interested in learning new things?
		Do you enjoy beautiful things, like nature, art, and music?
	Emotional Stability	
		Are you relaxed during stressful situations?
		Do you tend to worry? (R)
		Do you get nervous easily? (R)
	Agreeableness	
		Do you forgive other people easily?
		Are you very polite to other people?
		Are you generous to other people with your time or money?
	Grit	
		Do you finish whatever you begin?
		Do you work very hard? For example, do you keep working when others stop to take a break?
		Do you enj(
Socio-emotional Skills	*Hostile Bias*	
		Do people take advantage of you?
		Are people mean/not nice to you?
	Decision Making	
		Do you think about how the things you do will affect your future?
		Do you think carefully before you make an important decision?
		Do you ask for help when you don't understand something?
		Do you think about how the things you do will affect others?
	Achievement Striving	
		Do you do more than is expected of you?
		Do you strive to do everything in the best way?
		Do you try to outdo others, to be best?
	Self Control	
		Do you spend more than you can afford?
		Do you do crazy things and act wildly?
	Fixed Versus Growth M	
		The type of person you are is fundamental, and you cannot change much.
		You can behave in various ways, but your character can not really be changed.
		As much as I hate to admit it, you cannot teach an old dog new tricks. You cannot change their most basic properties.
		You have a certain personality and not much can be done to change that.

Note: Items and scales in blue are personality trait measures, items and scales in orange are socio-emotional skill measures.

Analysis Strategy

[13] All items except the Fixed Versus Growth Mindset items were scaled using a 4-point Likert scale (1 = Almost always – 4 = Almost never). The Fixed Versus Growth Mindset items employed a 6-point Likert scale (1 = Totally agree – 6 = Strongly disagree). Items that are marked with an (R) were reverse coded so that a low value indicates the same valence of response on every item.

Our initial analyses revealed three main issues with the data. First, correlations between items in the same groupings (e.g., openness, grit) were low – generally ranging from .2 - .4 – suggesting that each item is measuring a different facet of the grouping. Second, sum-scoring items according to the 11 hypothesized constructs and computing reliability coefficients indicated the scores were composed of a significant degree of measurement error. Third, the distribution of item responses across the Likert scales deviated substantially from normality, invalidating the assumptions inherent in traditional statistical measurement techniques. To address these issues, factor analyses were conducted in a multi-step process.

Results

The initial EFA revealed two groupings of items: those that loaded well onto one factor, and those that did not. The 4 items making up the original construct of "Fixed Versus Growth Mindset" loaded cleanly onto one factor. This factor was left intact and removed from the exploratory analyses; it was subsequently confirmed to provide a good fit to the data (χ^2 (2) = 27.52, CFI: .996, RMSEA: .057, .039 < 95% CI < .077).[14] Also removed from analyses at this juncture were items that loaded below .2 on any construct and items that were reverse coded due to factor-item correlations in unexpected directions. We then chose a 4-factor solution to model associations between the remaining 18 items; in this solution, items were allowed to cross-load on multiple factors and factors were allowed to correlate.[15] This model provided an excellent fit to the data (χ^2 (87) = 530.89, CFI=.985, RMSEA=.036, .033 < 95% CI < .039) while modeling the observed indicators parsimoniously.
The four identified factors described in Table 2, below, were: (1) Openness to New Ideas and People (5 items; e.g., "Are you outgoing and sociable?"; "Are you interested in learning new things?"); (2) Workplace Attitude and Behavior (5 items; e.g., "Do you enjoy working on things that take a very long time to complete?"; "Are people mean/not nice to you?"); (3) Decision Making (5 items; e.g., "Do you think about how the things you do will affect others?"; "Do you think carefully before making an important decision?"); and (4) Achievement Striving (3 items; "Do you do more than is expected of you?"). As detailed above, confirmatory factor analysis confirmed the fit of this model (χ^2 (129) = 2336.52, CFI=.922, RMSEA=.066, .064 < 95% CI < .069). In addition, preliminary measurement equivalence analyses indicate that this same factor structure provides a good fit to the data in Uzbekistan, Kyrgyzstan, and Tajikistan (χ^2 (459) = 69484.24, CFI=.932, RMSEA=.068, .066 < 95% CI < .070).[16]

[14] In assessing model goodness of fit, the following criteria are used: A RMSEA < .08 provides an acceptable fit to the data, while an RMSEA < .05 provides a good fit to the data; a CFI > .9 provides an acceptable fit to the data while a CFI > .95 provides a good fit to the data (Kline, 2011).
[15] Factor correlations in the final EFA ranged from .1 to .65. The highest correlations were: Openness-Decision Making (.535), Openness-Achievement Striving (.556), and Decision Making-Achievement Striving (.65).
[16] Tests of measurement invariance seek to establish whether we are measuring the same construct in the same way across different groups. As of this writing, our preliminary analyses have established *configural invariance:* that the same factor structure (e.g., the same number of factors and the same pattern of loadings) exists in the samples from all three countries. Future analyses will examine other levels of invariance, establishment of which increases our certainty that observed differences between countries is attributable only to true differences in the variability of the scores.

Table 2. Unstandardized Results from Final CFA of Non-Cognitive Skills Module

		Loading	SE
Extraversion			
1	Are you talkative?	0.502	0.015
2	Are you outgoing and sociable, do you make friends easily?	0.672	0.012
3	Are you interested in learning new things?	0.635	0.013
4	Do you enjoy beautiful things, like nature, art, and music?	0.528	0.015
5	Are you very polite to other people?	0.648	0.013
Workplace Attitudes and Behaviors			
6	Do you come up with ideas others haven't thought of before?	0.575	0.019
7	Do you work very hard? For example, do you keep working when others stop to take a break?	0.693	0.018
8	Do you enjoy working on things that take a very long time to complete?	0.506	0.019
9	Do people take advantage of you?	0.36	0.02
10	Are people mean/not nice to you?	0.207	0.024
Decision Making			
11	Do you finish whatever you begin?	0.622	0.013
12	Do you think about how the things you do will affect your future?	0.673	0.011
13	Do you think carefully before you make an important decision?	0.683	0.011
14	Do you ask for help when you don't understand something?	0.592	0.013
15	Do you think about how the things you do will affect others?	0.669	0.011
Achievement Striving			
16	Do you do more than is expected of you?	0.587	0.014
17	Do you strive to do everything in the best way?	0.723	0.013
18.	Do you try to outdo others, to be best?	0.463	0.016
Fixed Versus Growth Mindset			
19	The type of person you are is fundamental, and you cannot change much.	0.678	0.009
20	You can behave in various ways, but your character can not really be changed.	0.711	0.009
21	As much as I hate to admit it, you cannot teach an old dog new tricks. You cannot change their most basic pro	0.697	0.008
22.	You have a certain personality and not much can be done to change that.	0.704	0.008