Mohamed Ihsan Ajwad, Joost de Laat, Stefan Hut, Jennica Larrison, Ilhom Abduloev, Robin Audy, Zlatko Nikoloski and Federico Torracchi

The skills road : skills for employability in the Kyrgyz Republic

Report

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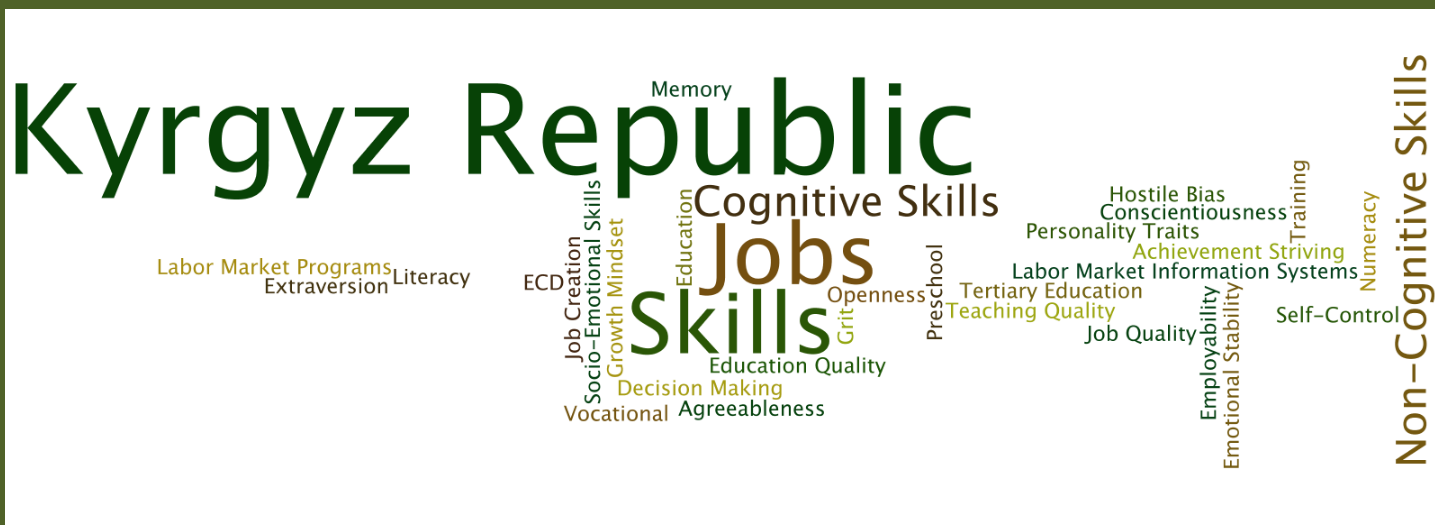
The Skills Road

Skills for Employability in the Kyrgyz Republic



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Abbreviations and Acronyms

BEEPS	Business Environment and Enterprise Performance Surveys
BNPP	Bank Netherlands Partnership Program
ECD	Early Childhood Development
EDS	Education Development Strategy
ETF	European Training Foundation
GIZ	German Society for International Cooperation
ILO	International Labor Organization
LMP	Labor Market Program
OECD	Organization for Economic Co-operation and Development
OJT	On the Job Training
PISA	Program for International Student Assessment
SMS	Short Message Service
SOE	State-Owned Enterprise
STEP	Skills toward Employment and Productivity
WDR	World Development Report

Acknowledgements

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The survey was implemented jointly by a team from the World Bank and the German Society for International Cooperation (GIZ). The project was conducted with generous support from Bank Netherlands Partnership Program (BNPP) for the "Skills for Competitiveness and Growth: The Challenge of Labor Exporting Countries" Initiative, led by Joost de Laat. The cognitive and non-cognitive skill scores were constructed by Carly Tubbs (Consultant, New York University), and Louise Bahry (Consultant, University of Massachusetts Amherst).

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Overview

In an increasingly interconnected and globalizing world economy, newly created jobs require a higher degree of analytical and interpersonal skills. With a per capita GDP in 2012 of US$1,155, the Kyrgyz Republic is a low-income country. However, it is experiencing a number of structural changes with the size of the industrial and service sectors—especially the latter—strongly on the rise. Detailed data analysis confirms that these sectoral shifts are changing the demand for skills in the Kyrgyz Republic toward "new economy skills." More generally, the Kyrgyz aspiration to become a middle-income economy will require a labor force that has diverse high-quality skills.

The goal of this report is to provide an in-depth analysis of the links that exist in the Kyrgyz Republic between education, skills, and labor market outcomes. The analysis builds on a unique household survey—the first ever conducted in the country—that goes beyond the traditional data and analysis on educational attainment. More specifically, the survey includes large-scale assessments of cognitive and non-cognitive skills of workers in both the formal and informal sectors, job seekers, and those who are inactive by testing and interviewing respondents. This is a relatively rare occurrence in middle- and low-income countries, though OECD countries tend to conduct these assessments more frequently.

The survey was developed specifically for this study and was conducted jointly by the German Society for International Cooperation (GIZ) and the World Bank in 2013 (see Box 1). The study was conducted with generous support from the Bank Netherlands Partnership Program (BNPP) for the "Skills for Competitiveness and Growth: The Challenge of Labor Exporting Countries" Initiative. The report complements and builds on past studies on the determinants of economic growth and the determinants of employment outcomes.[1]

The study contributes to the National Sustainable Development Strategy for the Kyrgyz Republic (2013–2017) by offering: (i) a detailed empirical assessment of the links between education and skills and between skills and jobs; and, (ii) specific policy goals deserving of particular attention when promoting job-relevant skills development over the life cycle.

The main finding of the report is that skills are valued in the labor market, yet skills gaps persist. Three findings are particularly noteworthy. First, youth with more cognitive and non-cognitive skills are more likely to be employed than inactive or discouraged people. Second, among the employed, workers with higher cognitive and non-cognitive skills are more likely to use those skills in their daily work. Third, among the employed, workers with higher skills—cognitive skills especially—tend to have higher quality jobs.

However, the report shows that there are weaknesses in the way skills are formed. While skills are developed during different stages in the life cycle and a host of actors are involved—families, for example, play a central role—the Kyrgyz education system has a mixed record in skill formation. First, three quarters of 3- to 5-year-olds lack access to preschools, raising concerns over the formation of cognitive and non-cognitive skills at an early age. Second, while education completion rates are generally high, about half of the youth entering the labor market with at most a secondary general education lack the cognitive, non-cognitive, and technical skills

[1] Arias et al. (2014), Sondergaard and Murthi (2012), Gill et al. (2014), World Bank (2012), and World Bank (forthcoming).

needed to secure quality jobs. Moreover, too many tertiary graduates have skill levels that are comparable to the skill levels of secondary general graduates. On the one hand, workers with higher educational attainment generally have higher cognitive and non-cognitive skills. On the other hand, there is considerable variation in cognitive skill levels across workers with identical educational attainment levels.

As discussed earlier, the detailed analysis of skills in the Kyrgyz Republic is a unique feature to this report. This report defines workers' skills as cognitive, non-cognitive (social and behavioral), and technical skills. This study focuses on cognitive and non-cognitive skills. Cognitive skills capture the ability to use logical, intuitive, and critical thinking as well as skills such as problem solving, verbal ability, and numeracy. The cognitive skills measured in this report include memory, literacy, and numeracy skills. Non-cognitive skills represent personality traits and socio-emotional skills that are relevant in the labor market, including extraversion, conscientiousness, openness to experience, agreeability, and emotional stability. This survey measures the following non-cognitive skills: openness/sociability, workplace attitude, decision making, achievement striving, and growth mindset.

There is considerable scope for public policy to address the observed skills gaps. Policies can target the future workforce, usually by focusing on families and communities and focusing on the formal education system, and/or target the current workforce, by focusing on adult training institutions and on-the-job training by firms. Taken together, the Kyrgyz findings and the Skills Toward Employment and Productivity (STEP) Framework point to three policy goals that can strengthen the quality, relevance, and use of skills over the life-cycle:

- *To get children off to the right start:* by continuing to emphasize public policies that seek faster universal access to early childhood development services, building on the nutrition and preschool strategies, and the recent findings from the institutional SABER ECD review[2] (see Appendix F: SABER ECD 2013—Summary of policy options to improve ECD in the Kyrgyz Republic). These efforts should be promoted as an integral part of a strategy to build strong skills for the future.
- *Ensuring that all students learn* and *build job-relevant skills that employers demand:* by building on public policies, such as the education development strategy (EDS 2020), that: (i) seek to build strong non-cognitive skills at all education levels, alongside strong cognitive skills; (ii) promote non-cognitive skill building in schools; (iii) emphasize systematic measurement of skills alongside education and labor market outcomes; (iv) encourage more students to invest in technical/science training, both at the secondary and tertiary level.
- *Encouraging entrepreneurship and innovation:* by emphasizing public policies that: (i) encourage firms to enhance skills use and skills investments; (ii) support migrants to build more skills to increase their earning capacity and therefore their ability to support their families.

This report begins by examining the characteristics of the Kyrgyz labor market, examining in particular emerging signs that the demand for skills is structurally changing, alongside patterns of labor market participation and the quality of jobs. Section 2 explores the demand for and use of cognitive and non-cognitive skills in the Kyrgyz labor market. Section 3 then examines the formation of skills to determine whether the education system is effectively imparting the cognitive and non-cognitive skills demanded by

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[2] http://wbgfiles.worldbank.org/documents/hdn/ed/saber/supporting_doc/CountryReports/ECD/SABER_ECD_Kyrgyz_Republic_CR_Final_2013R.pdf.

employers. The report concludes with a discussion of public policies within the STEP framework to build skills that meet the Kyrgyz aspiration to become a middle-income country.

Box 1: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey* (2013)

The Jobs, Skills, and Migration survey is one of three identical household surveys conducted in Central Asia in 2013 by the World Bank in collaboration with GIZ. The countries covered are the Kyrgyz Republic, Uzbekistan, and Tajikistan.[+] It is representative at the national, regional (Oblast), and urban/rural level. The survey collected comprehensive information not typically captured by traditional household surveys. It includes two distinct instruments: a core questionnaire and a skills questionnaire. The sample size of the core questionnaire was 1,500 households with a total of 7,706 individuals. Given that one individual per household was randomly selected to partake in the skills questionnaire, this sample consists of 1,500 individuals. The survey was conducted from July to September, 2013.

*1. Core questionnaire**

The core questionnaire contains modules on education, employment, migration, health expenditure, remittances, government transfers, financial services, subjective poverty, and housing conditions, as well as a complete household expenditure module. The core questionnaire concludes with the random selection of a household member aged 15 to 64 to whom the skill questionnaire is administered. The random selection is based on a random number table (Kish grid).

*2. Skills questionnaire**

The skills questionnaire contains detailed modules on labor and work expectations, migration and preparation for migration, language skills, and technical skill training. A unique aspect of the survey are the cognitive and non-cognitive questions to test skills. The cognitive skills module is based on a recent instrument developed for a similar survey in Bulgaria. 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 labor markets.

[+] See Ajwad et al. (2014), "The Skills Road: Skills for Employability in Tajikistan," and Ajwad et al. (2014), "The Skills Road: Skills for Employability in Uzbekistan."

* A more detailed overview of the questionnaire sections is available in Appendix A: Questionnaire Sections.

1 Structural Changes and the Labor Market

This section presents labor market outcomes in the Kyrgyz Republic and attempts to answer three fundamental questions:

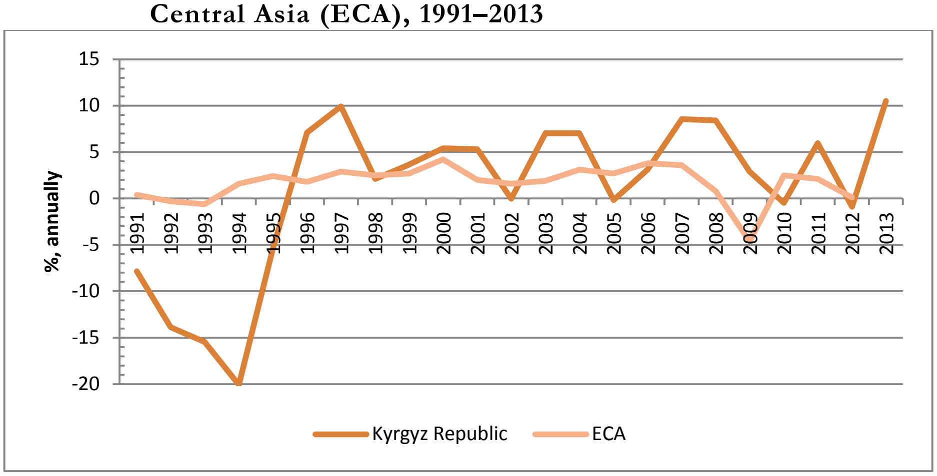
1) Are there signs that the demand for skills is structurally changing?
2) How does labor market participation compare across cohorts and gender?
3) What do we know about job quality in the Kyrgyz Republic?

The section that follows explores whether and how labor market participation and access to quality jobs are related to individual skill levels and skill composition in the Kyrgyz Republic. In addition to the results presented in the main body of the report, Appendix D: Summary Tables contains more detailed results on labor market outcomes.

1.1 Structural transformations are changing the demand for skills

After a dramatic decline in economic growth following independence, the Kyrgyz Republic experienced positive, albeit volatile, economic growth (Figure 1). Before 1991, the Kyrgyz Republic created products exclusively for the Soviet Union. However, with the dissolution of the U.S.S.R., demand for production disappeared and many industries closed. In the absence of alternative markets, agriculture and service sectors began to increase, and growth rebounded by the mid-1990s. GDP growth averaged 3.7 percent between 2002 and 2012. With a per capita GDP in 2012 of US$1,155[3], the Kyrgyz Republic is a low-income country. While, on average, GDP growth rates have been positive, internal conflict has created a volatile growth environment over the last four years, with growth rates ranging from negative one percent to 10 percent.

Figure 1: GDP growth in the Kyrgyz Republic has been unstable compared to Europe and Central Asia (ECA), 1991–2013



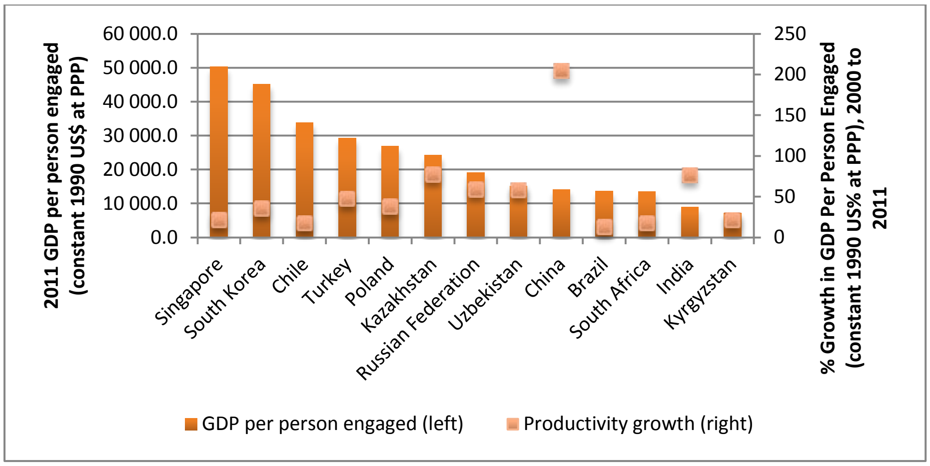
Source: World Bank, World Development Indicators, 2013 data from Kyrgyz authorities.

Labor productivity remains low, however, and formal job creation has remained well below population growth. Between 1996 and 2012, formal employment rates grew at an average rate of only 0.14 percent per

[3] World Development Indicators, World Bank, 2012 series, current USD.

year, while the population grew at a rate of 1.2 percent per year. The number of individuals entering the labor market is disproportionately larger than formal job creation. Between 60,000 and 75,000 vacancies must be created annually to absorb graduates entering the workforce; in reality, as few as 25,000 new vacancies a year may actually be available in the Kyrgyz labor market (Kyrgyzstan Country Programme on Decent Work for 2010–2014; European Training Foundation, 2013). This equates to a vacancy for only one in three graduates. Furthermore, labor productivity growth averaged less than two percent between 2000 and 2011 (Figure 2). Comparatively, productivity growth averaged over four percent in Turkey and over five percent in Russia for the same time period. Improving productivity rates are essential to accessing potential economic and social gains.

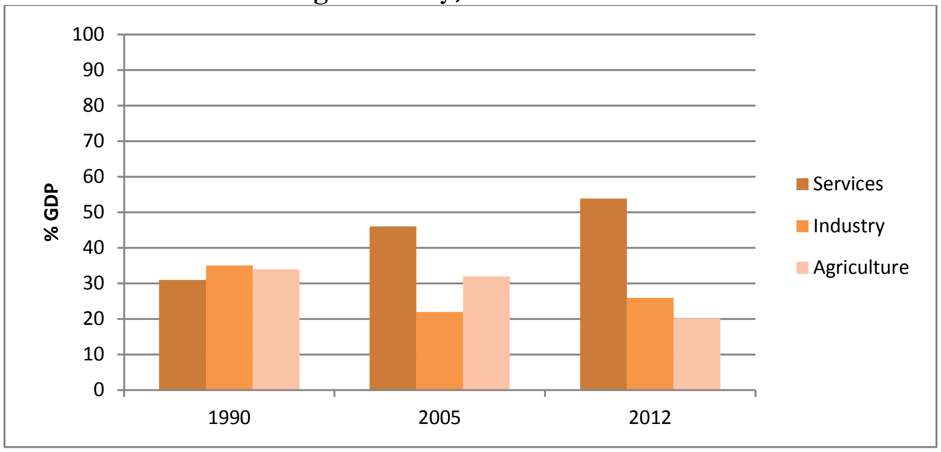
Figure 2: Productivity has grown slowly and remains behind other comparator countries, 2000–2011



Source: ILO (2013).

Nevertheless, the structure of Kyrgyz economy has changed markedly over the past 20 years. In 1990, the service, industry, and agricultural sectors each accounted for approximately one-third of GDP, with industry being marginally the largest. The industrial sector largely collapsed after transition, but has begun a revival in the last few years with the garment industry and private enterprises expanding. While agriculture became the dominant sector in the 1990s, more recently agriculture has been replaced by the service sector. Today, the service sector accounts for approximately 54 percent of GDP, as compared to 26 percent for the industry sector and 20 percent for agriculture (Figure 3).

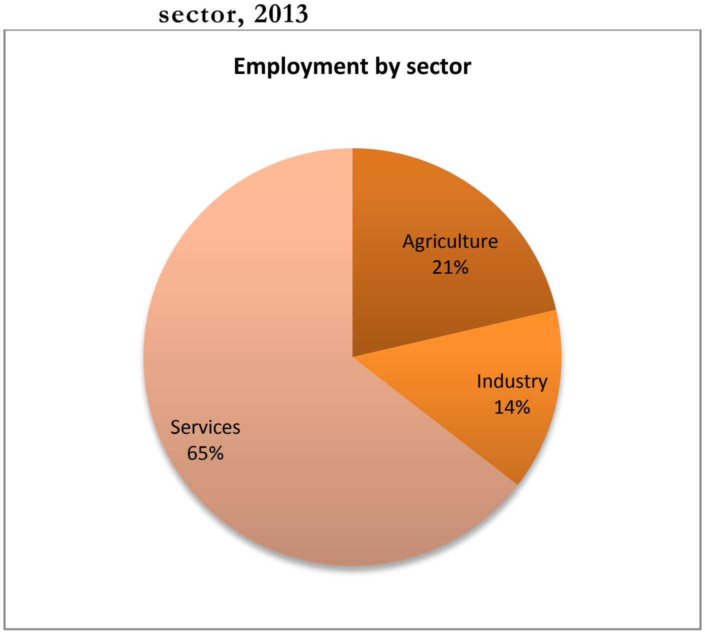
Figure 3: The share of agriculture in GDP has declined, while the share of services has increased significantly, 1990–2012



Source: World Bank, World Development Indicators.

Currently, the majority of people with jobs work in the service sector. Sixty-four percent of the labor force works in the service sector, 14 percent in industry, and 22 percent in agriculture. Thus, given their sectoral shares in GDP, the share of agriculture in GDP is largely equivalent to its share in employment, while the economic contribution in industry exceeds its workforce contribution and service productivity lags. Gender disparities are prevalent in the industry sector, where 88 percent of workers are male. In many countries that similarly undergo a process of structural shift, whereby jobs are shifted away from the traditional sectors (agriculture and mining) to more modern sectors (industry and services), this shift implies a rise in importance of the cognitive and non-cognitive skills in the economy (OECD, 2010).

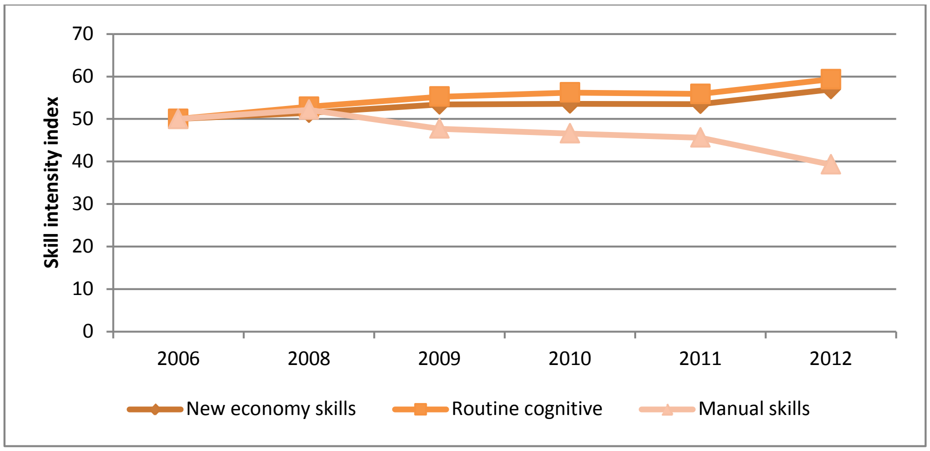
Figure 4: The majority of individuals in the Kyrgyz Republic are employed in the services sector, 2013



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Sectoral shifts have also been accompanied by a greater demand for "new economy skills," as evidenced by an analysis[4] of Kyrgyz Household Budget Surveys between 2006 and 2012. New economy skills are higher-order analytical and organizational skills, including non-routine cognitive analytical and interpersonal skills. Figure 5 illustrates the change in an index of the skills intensity of jobs relative to 2006, measured in "centiles" (or less precisely, the percentile change in skills requirements in jobs in the Kyrgyz economy). The graph shows that new economy skills have risen since 2009, with the largest increase between 2011 and 2012. In addition, the demand for routine cognitive skills has shown a subtle increase as well. New economy skills and routine cognitive skills are often associated with services and manufacturing jobs. Meanwhile, the demand for routine manual skills—often associated with low productivity agriculture and retail occupations—declined moderately. This shift in skills demand is consistent with shifts observed in other Eastern European and Central Asian countries, as well as in many OECD countries, although the trends are more muted in the Kyrgyz Republic.

Figure 5: The evolution of skill intensity reveals an increase in "new economy" skills, 2006–2012



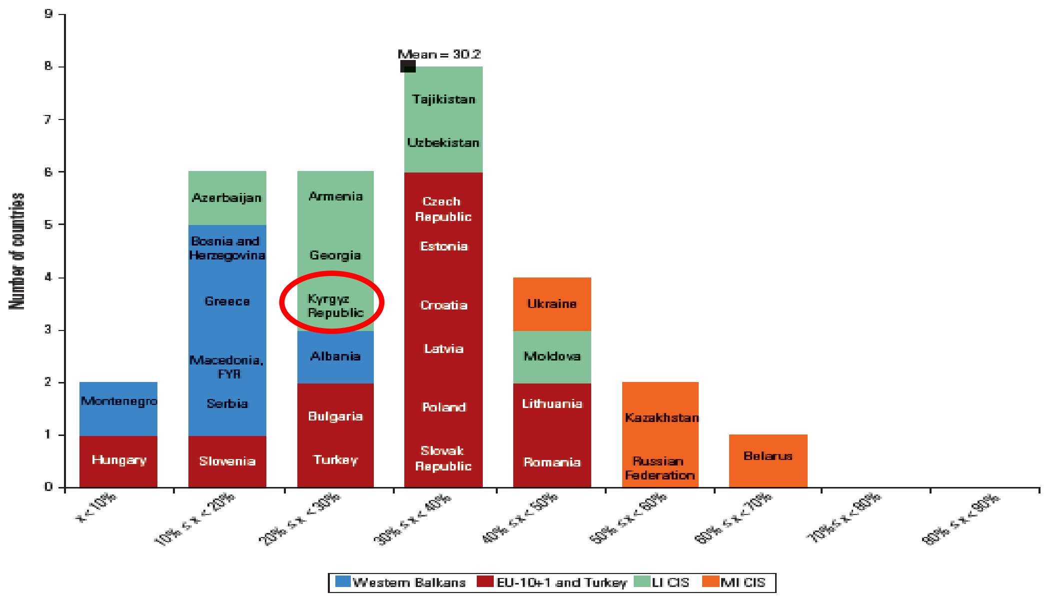
Source: Authors' estimates using the Kyrgyz Republic Household Budget Survey, 2006–2012.

In line with this shift, firms increasingly report that workers are not adequately prepared for the demands of the labor market. In 2008, between 20 and 30 percent of businesses across the manufacturing, services, and construction sector in the Kyrgyz Republic claimed that lack of skills was a major or very severe constraint to their business (Figure 6), placing the Kyrgyz Republic below the mean in Eastern Europe and Central Asia. However, in the 2013 World Bank Enterprise Survey, 33 percent of firms identified an inadequately educated workforce as a major constraint in the Kyrgyz Republic, significantly higher than the Eastern Europe and Central Asia average of 22 percent. This level of employer dissatisfaction across sectors represents a real concern regarding skills.[5]

[4] The analysis relies on a methodology first developed by Autor, Levy, and Murnane (2003) and expanded by Acemoglu and Autor (2011). It employs the skills requirement of different occupations in the United States as a benchmark, defined by the O*NET dictionary of occupations. A given job can, on a skill of 1 to 5, require skills in four categories: new economy skills, non-routine manual/physical skills, routine cognitive, and routine manual.

[5] Arias et al. (2014).

Figure 6: Skills are a constraint for employers in the Kyrgyz Republic



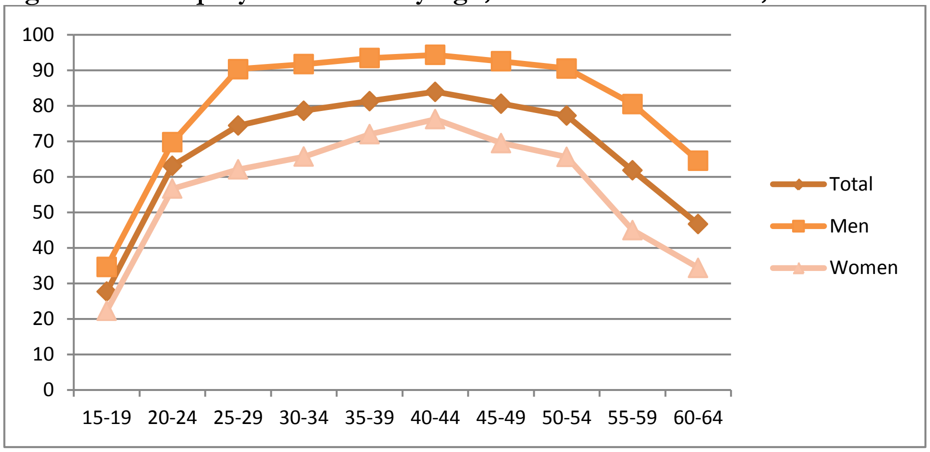
Source: Sondergaard et al. 2012, based on BEEPs (Business Environment and Enterprise Performance Surveys).
Notes: The percentages on the x-axis are the shares of enterprises in the relevant bars that say skills are a major or very severe constraint to their business. EU-10+1 comprise the new member states of Eastern Europe and Croatia. LI are low-income and MI are middle-income countries of the Commonwealth of Independent States (CIS). See the data table in annex 4B for the key to abbreviations of country names.

1.2 The high employment rate bodes well for overall skills use

The labor force of the Kyrgyz Republic is young and the overall employment rate is relatively high. The population currently stands at 5.6 million with a growth rate of 1.1 percent per annum.[6] Over 60 percent of the population is under the age of 30 and half of all individuals in the Kyrgyz Republic is under 15 years of age, which is double the proportion among EU countries. Less than five percent of the population is over 65, compared to 19 percent in EU countries. The employment rate measures the share of the labor force aged 15-64 years in jobs, and is therefore a first indicator of skills use: those people not in jobs are unable to use their skills to contribute to the economy. The survey data show that 82 percent of men aged 15–64 and 59 percent of women are working, comparing favorably with rates of 73 percent and 58 percent, respectively, in OECD countries.

[6] United Nations Statistics Division, 2012.

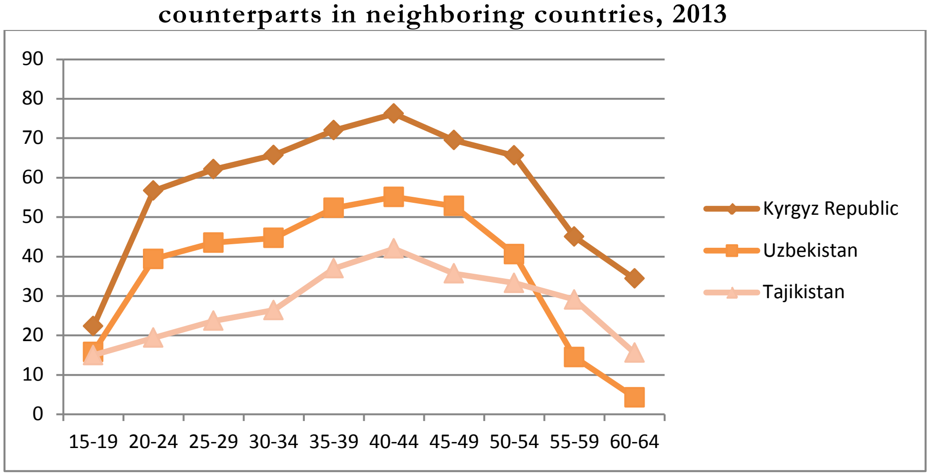
Figure 7: Employment rates by age, for men and women, 2013



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.

The Kyrgyz female employment rate (59 percent) is much higher than in Uzbekistan (40 percent) and Tajikistan (29 percent). Female participation rates are relatively similar for 15-19 year olds in the Kyrgyz Republic, Uzbekistan, and Tajikistan. However, by age 20, marked variations in labor participation across countries appear and remain throughout the prime working years (Figure 8). Overall, Uzbekistan and Tajikistan have female employment rates of approximately 40 percent and 29 percent, respectively, compared to 59 percent in the Kyrgyz Republic.

Figure 8: Women in the Kyrgyz Republic are more active in the labor market than their counterparts in neighboring countries, 2013



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Migration is also an important dimension of the labor market in the Kyrgyz Republic. Five percent of the Kyrgyz population migrates domestically, while over 10 percent, or more than triple the world average (3.2 percent), is currently abroad (Table 1). Women are more likely to migrate domestically, while men are more likely to migrate internationally. Qualitative studies suggest that for youth, in particular, migration is viewed as an opportunity to find a job and obtain experience and skills, since their received education and training is not seen as providing the practical professional skills required for employment.[7]

[7] World Bank (2013b).

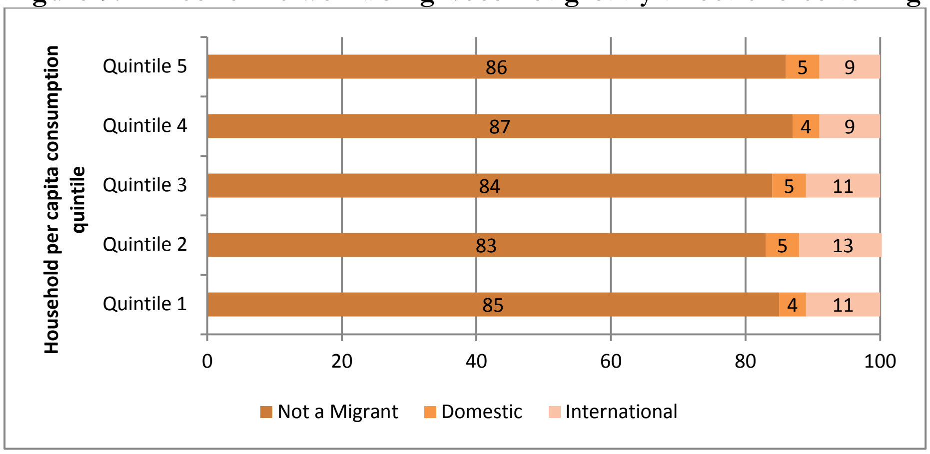
Table 1: Migration by type

	International	Domestic	Total
Female	6.7%	5.1%	11.8%
Male	14.7%	3.9%	18.6%
Total	10.5%	4.6%	15.1%

Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013, World Band staff calculations.

Research shows that generally the poor, but *not* the very poor, tend to migrate[8]; however, consumption levels appear to have less impact on the decision to migrate in the Kyrgyz Republic. All consumption levels have a relatively similar migration profile (Figure 9). While the second quintile, at 18 percent, is the most likely to migrate, 15 and 14 percent of the first and fifth quintiles migrate, respectively. This may be due largely to high levels of informality and the perceived benefits of working abroad.

Figure 9: Economic well-being does not greatly affect choice to migrate, 2013



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.

The Kyrgyz Republic is a member of regional and bilateral agreements regarding migratory movement, with the Russian Federation dominating as the destination of choice for Kyrgyz migrants. A regional agreement permits visa-free entry and waives requirements for pre-arrival employment guarantees to the Russia Federation. Over 80 percent of emigrants choose Russia as their destination. The Kyrgyz Republic further maintains bilateral agreements with Kazakhstan, Tajikistan, and Uzbekistan relating to the social protection of migrants.[9] As such, Kyrgyz also migrate to these neighboring countries. In addition, Ukraine, Israel, and Germany attract workers, though in substantially smaller numbers. The majority of migrants are involved in individual entrepreneurship, travelling back and forth to sell goods; however many are also recruited to work in agriculture, construction, department stores, and cafes.[10] Remittances accounted for almost one-third of GDP in 2012, making migration more productive than any other sector given the percent of population involved. The most lucrative remittances come from the Russia Federation (US$2,308 million), Israel (US$80 million), and Ukraine (US$74 million).[11]

[8] Murrugarra et al. (2011).
[9] Chudinovskikh (2012).
[10] ILO (2010).
[11] World Bank (2013c).

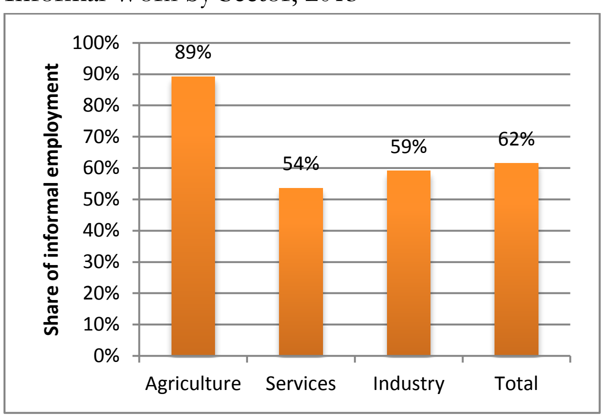
Migrants may also face job insecurity abroad, often exacerbated by work in the informal sector or illegal residency in destination countries. In a recent survey, approximately one-third of migrant workers report that they are working illegally in their host country. The same survey found that an estimated 61 percent of migrant workers have not signed a written employment contract, and are thus excluded from the worker protections guaranteed through existing bilateral labor agreements.[12] Low-skilled migrants in particular are likely to work without the security of a contract.

1.3 Job quality remains a serious concern for effective skills use

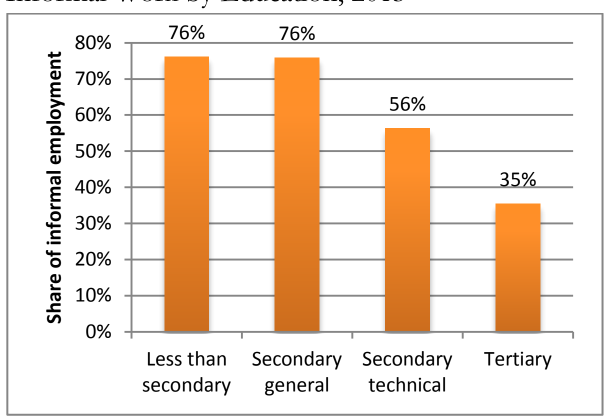
Informality is extremely high, raising concerns regarding the effective use of skills. Informality is defined as those who lack an employment contract or are unpaid family workers (similar to other research in Europe and Central Asia). As shown in Figure 10, almost two thirds (62 percent) of Kyrgyz workers hold an informal job. Nearly all individuals with only a secondary general education end up working in the informal sector (76 percent). Informality, while still extremely high, is the lowest in the service sector: 54 percent are working informally, compared with 59 percent of industry workers and 89 percent of workers in agriculture. Informality generates several challenges as workers without a formal contract must overcome multiple barriers in managing shocks and risks (e.g. Koettl et al., 2012). Furthermore, other studies have shown that as small informal businesses lack access to credit, they also often lack the means to make the type of capital investments that complement the human capital skills and enhance their effective use. And, they have fewer incentives to invest in worker training.

Figure 10: Informal salaried work is particularly common in the agricultural sector and for individuals with a secondary general or less than secondary education

Informal Work by Sector, 2013



Informal Work by Education, 2013



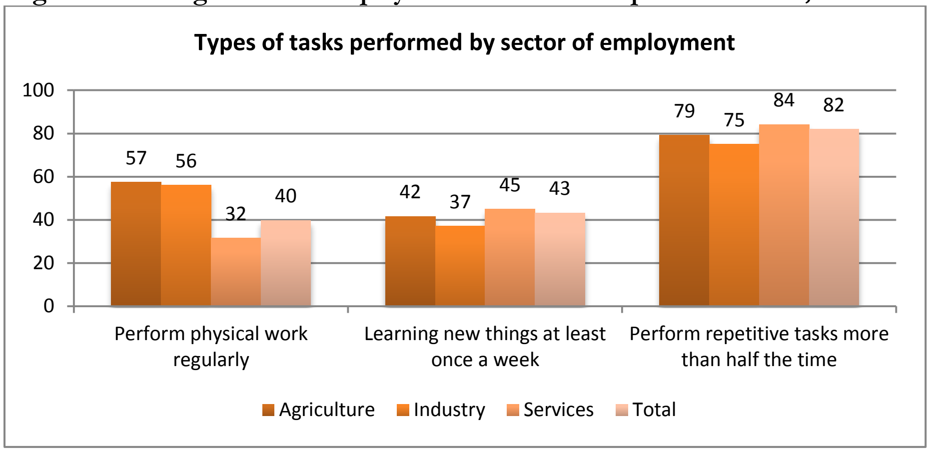
Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.

Overall, a large share of workers in the Kyrgyz Republic perform physical tasks and few workers learn new things on the job (Figure 11). In this study, physical work is defined as regularly lifting or pulling anything weighing at least 50 pounds (25 kilograms). Physical work is unsurprisingly common in the agricultural and industrial sectors, and less so in the services sector. The majority of tasks performed at work are repetitive in nature (82 percent), which holds for jobs in all three sectors. Manual, repetitive tasks limit the scope for on the job learning, which is confirmed by survey respondents in all three sectors. Only about 42 percent of all

[12] Ajwad et al. (2014); OECD (2012a).

respondents working in agriculture and 37 percent in industry state that they learn new things at least once a week. This share is slightly higher, at 45 percent, in services.

Figure 11: High shares of physical work and repetitive tasks, 2013

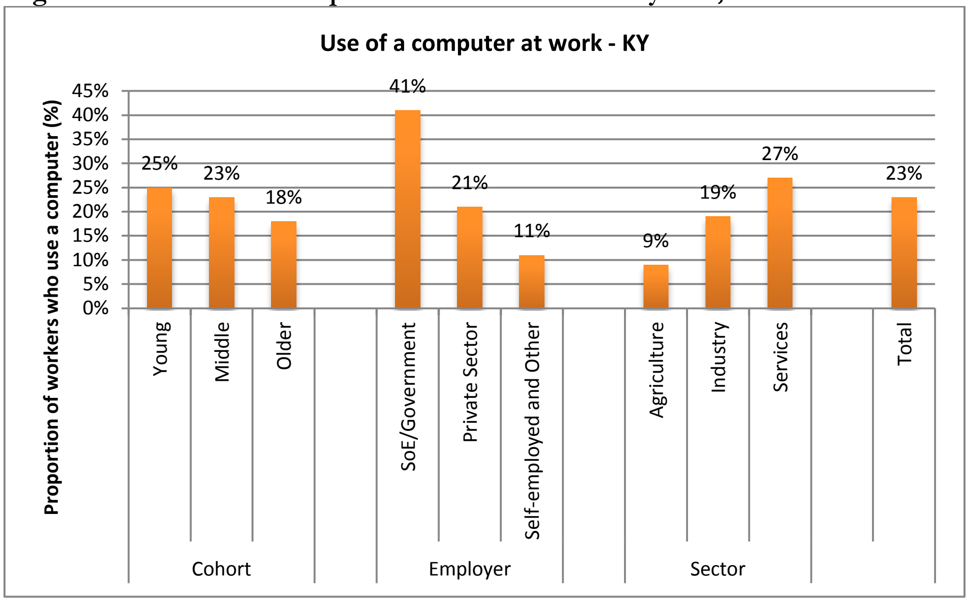


Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.
Note: Performing physical work is defined as regularly lifting or pulling anything weighing at least 50 pounds (25 kilograms).

Overall, computer use is relatively low in the Kyrgyz Republic. As shown in Figure 12, 27 percent of service sector workers use computers at work, compared with 19 percent in industry, and 9 percent in agriculture. Furthermore, a higher proportion of young workers (25 percent) uses computers compared with older workers (18 percent). Again, however, while the shift toward services is being accompanied by increased demand for more complex skills (here: computer use), the overall level of complex skill use is relatively low compared with other developing countries. Whereas computer use in Kyrgyz stands at 23 percent, in the Yunnan province in China 55 percent of workers use computers, in Bolivia and Vietnam 35 percent use computer, and in Sri Lanka 30 percent or workers use computers.[13]

[13] World Bank (2013e).

Figure 12: Use of a computer at work is relatively low, 2013



Source: Authors' estimates using World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.

2 Better Skills Are Good Predictors of Labor Market Outcomes

This section presents findings about the returns to skills in the labor market and the use of skills on the job in the Kyrgyz Republic, and addresses two fundamental questions:

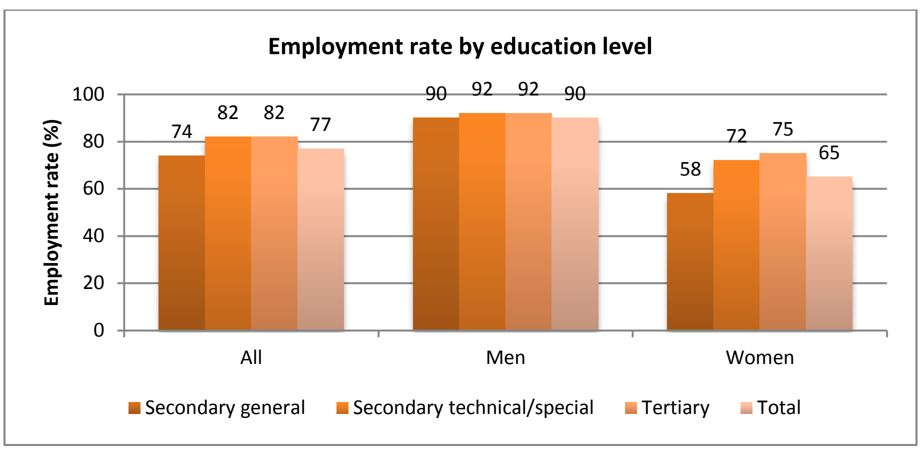
1) What skills are valued in the labor market; and
2) What skills do workers currently use?

In addition to the results presented in the main body of the report below, Appendix E: Cognitive and Non-Cognitive Skill Mean Scores contains more detailed information on cognitive and non-cognitive skill outcomes.

2.1 Education is valued in the labor market

Employment rate increase with educational attainment. Among women, university and secondary special/technical graduates are more likely to work than graduates with secondary general education. Among men, employment rates are very high regardless of education levels. Overall, the employment rate among adults with a university degree is 77 percent, compared to 57 percent among adults with a secondary general education level. This positive correlation is fully driven by employment outcomes for women, however. Among men aged 25–54, employment rates are approximately 90 percent, regardless of the level of completed education, while 58 percent of female secondary graduates work compared with 72 and 75 percent among secondary technical/special and tertiary, respectively.

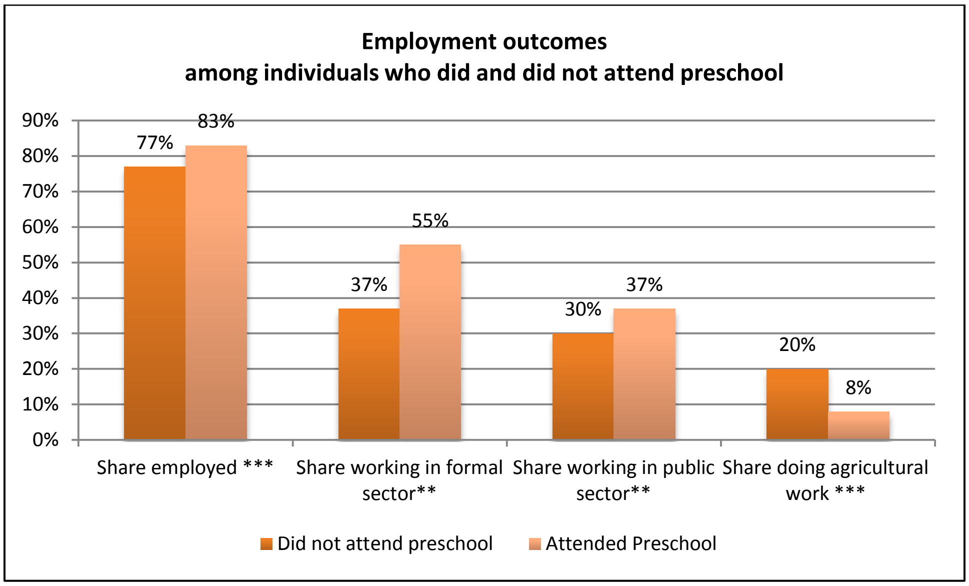
Figure 13: Tertiary graduates and secondary special/technical graduates have better labor market outcomes than individuals with a secondary general education, 2013



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey*, 2013.
Note: Respondents aged 25–64.

Preschool attendance correlates with a higher probability of being employed, as well as having a better job later in life, but mainly through higher educational attainment. While not implying causality, findings show that adults who attended preschool as a child on average are more likely to be employed (83 percent) compared to adults who did not attend preschool (77 percent). Among those employed, a larger share of adults who went to preschool as a child has a job in the formal sector (55 percent compared to 37 percent). Performing agricultural work is also less common among adults who went to preschool as a child. However, when taking into account demographic characteristics such as age, gender, marital status, area, and (most importantly) educational attainment, preschool is no longer a significant correlate of employment outcomes (Figure 14).

Figure 14: Employment outcomes are positively correlated with preschool attendance as a child, 2013

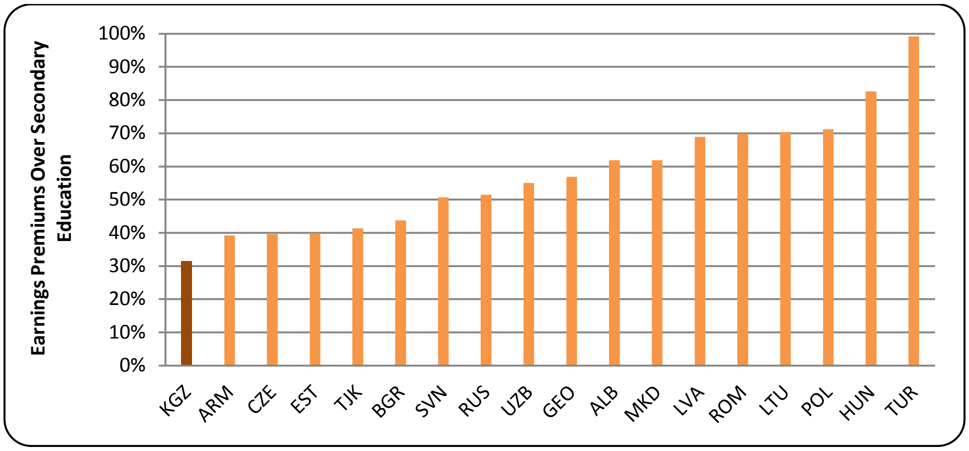


Source: Authors' estimates using World Bank/GIZ *Kyrgyzstan Jobs, Skills, and Migration Survey,* 2013.
Notes: Respondents aged 25–64; ***/**/* represent significant differences in outcome between individuals with and without preschool at the 1%/5%/10% significance level, respectively.

Among the employed, there is a modest wage premium to tertiary education. Figure 15 shows the average percentage earnings premium for workers with a tertiary education relative to workers with secondary education (both general and technical) with similar observed characteristics. On average, tertiary educated workers have a 30 percent higher wage than similar workers with secondary education. Such a return to tertiary education is a signal of a strong demand for tertiary educated individuals in the labor market. However, in comparison with other countries in ECA, the college premium is the lowest in Kyrgyzstan. There are two likely explanations. First, there is a relatively large supply of tertiary graduates: 27 percent of the working population has a tertiary degree, which is higher than the 23 percent average in OECD countries. Second, there is a positive correlation between the degree of modernization (reforms to transition to a market economy) and the returns to higher education.[14] Average college premiums are highest in most EU-10 countries. The value and importance of tertiary education is likely to increase as the Kyrgyz economy continues to modernize.

[14] See, for instance, Staneva et al. (2010); Flabbi et al. (2007); Rutkowski (1996 and 2001).

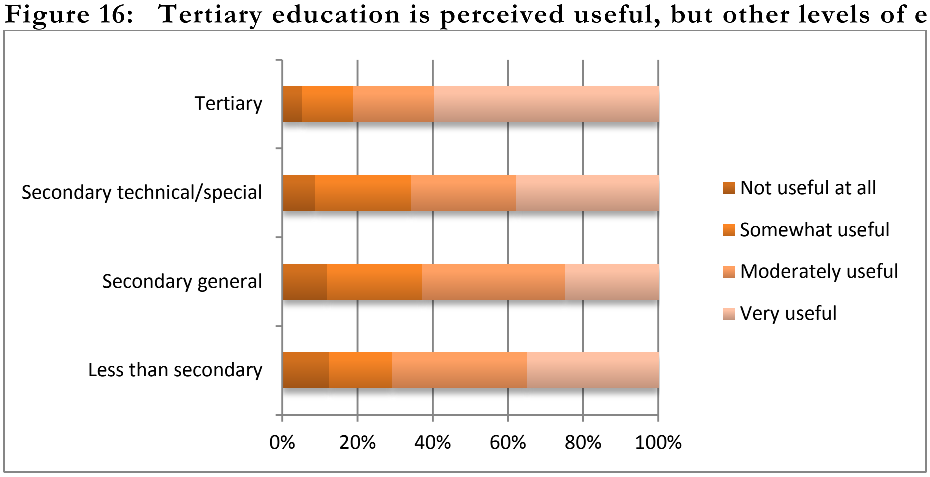
Figure 15: The average returns to higher education are significant among salaried workers aged 25–64 in the Kyrgyz Republic



Source: Authors' estimates using World Bank/GIZ *Tajikistan Jobs, Skills, and Migration Survey,* 2013; World Bank/GIZ *Uzbekistan Jobs, Skills, and Migration Survey,* 2013; World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013. Estimates for other countries in Arias et al. (2014).
Note: Salaried workers aged 25−64.

Workers' own perceptions regarding the usefulness of their education point to tertiary standing out favorably. Overall, tertiary graduates find their education the most useful with almost 60 percent responding that their education is very useful. Only 25 percent of individuals with a secondary general education report their education to be very useful, and less than 40 percent of secondary technical graduates find their education very useful for their job (Figure 16).

Figure 16: Tertiary education is perceived useful, but other levels of education less so



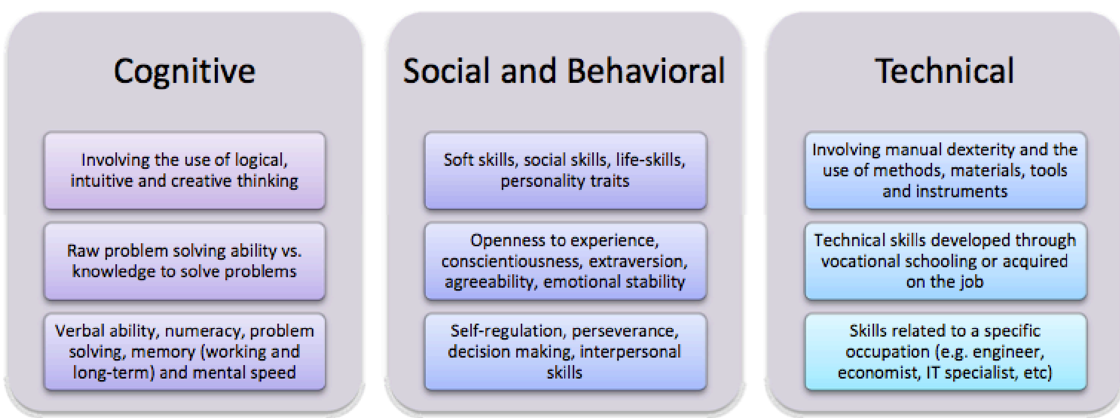
Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

2.2 Skills and employability are closely linked

Do skills matter? A well-functioning labor market values the skills imparted in the education system and not only the diplomas granted by the system. While employees may have sufficient education credentials—and education completion rates in the Kyrgyz Republic are high, as discussed below—employers may nonetheless complain that employees do not have the right skills for the job. Recent studies show that the quality of education (not the quantity) ensures that students develop valuable skills and matters to growth.[15]

A worker's skillset consist of three types of skills: cognitive skills, non-cognitive skills, and technical skills. Cognitive skills capture the ability to use logical, intuitive and critical thinking as well as skills such as problem solving, verbal ability, and numeracy. Non-cognitive skills represent personality traits that are relevant in the labor market, including extraversion, conscientiousness, openness to experience, agreeability, and emotional stability. Technical skills include the use of methods, materials, tools and instruments, and extend to specific skills relevant in particular occupations. Due to data limitations, this study focuses in particular on cognitive and non-cognitive skills (see Box 2 for more details).

Figure 17: A worker's skillset can be divided into three types of skills



Source: Pierre el al. (forthcoming), cited in World Bank (2013b).

[15] Hanushek and Woessmann (2008).

Box 2: Skills definitions in this study

The three cognitive skills measured in this study are memory, literacy, and numeracy. The working memory score is based on twelve items that asked respondents to repeat a sequence of numbers of increasing length. The literacy score represents reading comprehension skills and builds on five text comprehension questions about a story card. The informational numeracy score is built using a total of 10 questions measuring comprehension of a medicine instructions card, a bus schedule card, publicity, and a graph. It should be noted that the numeracy score represents various aspects of numeracy skills, which often also require a broader set of cognitive skills such as being literate. In particular, individuals with a high score on numeracy have the ability to recognize and manipulate numbers contained in and represented by various formats.

The five non-cognitive skills measured in this study are openness, workplace attitude, decision making, achievement striving, and the growth mindset scale. The skills are built using the following items:

(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?");

(4) Achievement Striving (3 items; e.g. "Do you do more than is expected of you?"; "Do you try to outdo others, to be best?"); and

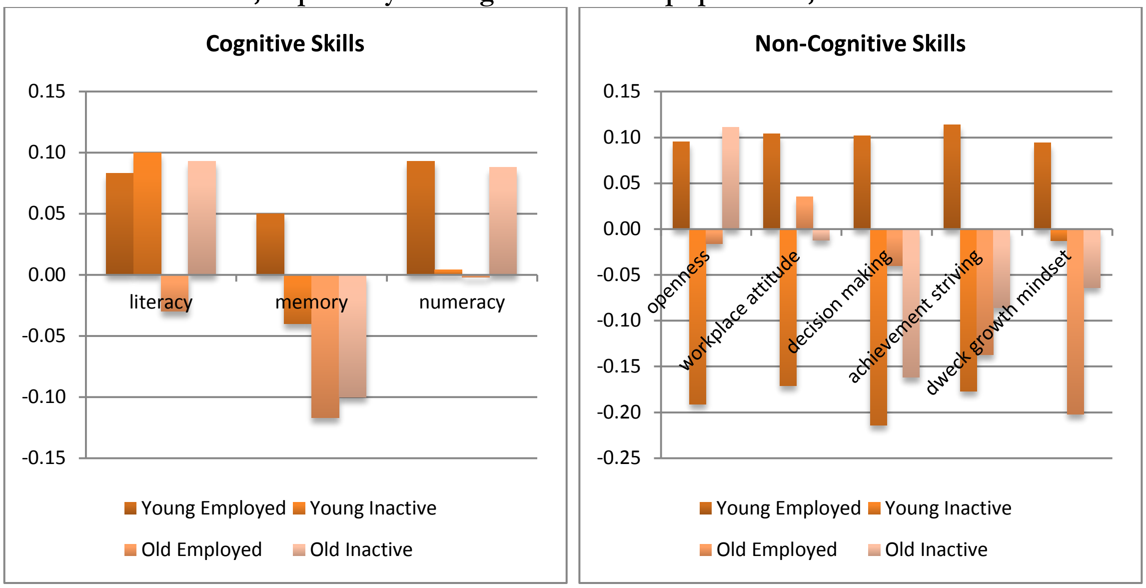
(5) Growth Mindset Scale (4 items; e.g. "The type of person you are is fundamental, and you cannot change much"; "You can behave in various ways, but your character cannot really be changed.").

* A detailed description of the cognitive scores and their construction is included in Appendix B: Constructing Cognitive Skills Scores Methods for Scale Development and Scoring.
** A detailed description of the non-cognitive scores and their construction is included in Appendix C: Constructing Non-Cognitive Skills Scores Methods for Scale Development and Scoring.

First, cognitive and non-cognitive skills correlate positively with finding a job. Figure 18 shows that young employed adults generally have considerably better cognitive skills—with the exception of literacy—and non-cognitive skills than young inactive adults. The same gap is not observed between older adults (aged 55–64) who are employed and older adults who are inactive, however, suggesting that inactivity among elder workers is driven by reasons other than skills. For example, responses from qualitative interviews suggest that personal ties are the most effective means for acquiring a job.[16] Furthermore, note that young employed adults score significantly higher on nearly all cognitive and non-cognitive assessments than both employed and inactive older adults. Notable exceptions are literacy and numeracy (cognitive) skills, and openness (non-cognitive) skills.

[16] World Bank (2013b).

Figure 18: Cognitive and non-cognitive skills are generally better in young compared to older workers, especially among the inactive population, 2013



Source: Authors' estimates using World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.
Note: Young adults are aged 25–34, old adults are aged 55–64.

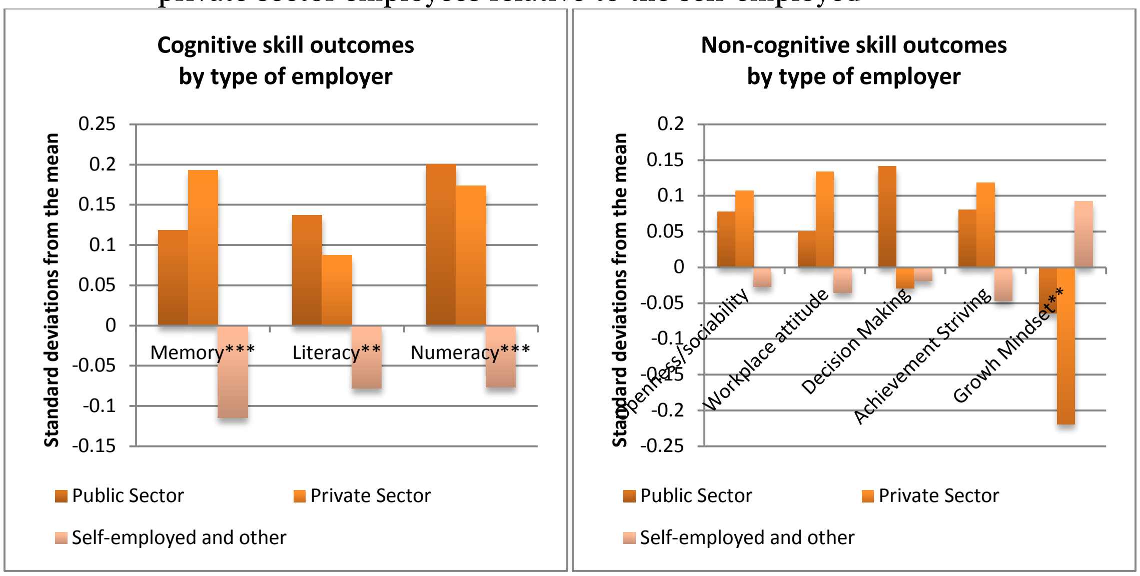
Box 3: Existing literature shows a strong relationship between both cognitive and non-cognitive skills and employment outcomes

Past work has shown a strong and robust relationship between cognitive skills and labor 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 et al., 2006). Moreover, the empirical evidence shows that a shortage of skills is considered to be one of the biggest barriers to employment (Sánchez Puerta, 2009). The empirical literature on cognitive skills/labor market outcomes distils two types of causal pathways: (i) direct—e.g. Murnane et al., 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 a higher level of education, which in turn leads to higher economic returns.

Similarly, there is growing evidence that non-cognitive skills are also important for labor market outcomes. Even though a more recent phenomenon, the empirical literature on the skills/labor market outcomes nexus finds a strong and robust relationship between certain non-cognitive skills, such as dependability, persistence, and docility and labor market outcomes (Heckman et al., 2006; Blom and Saeki, 2011; and Cunha and Heckman, 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).

All cognitive skills and most non-cognitive skills are higher among public and private sector employees relative to the self-employed. In order to explore the relationship between a respondent's skill set and the quality of the job, the analysis from above is repeated restricting it to employment in the state administration, SOEs as well as private enterprises employing more than 6 employees. The results below indicate that the self-employed consistently score lower.

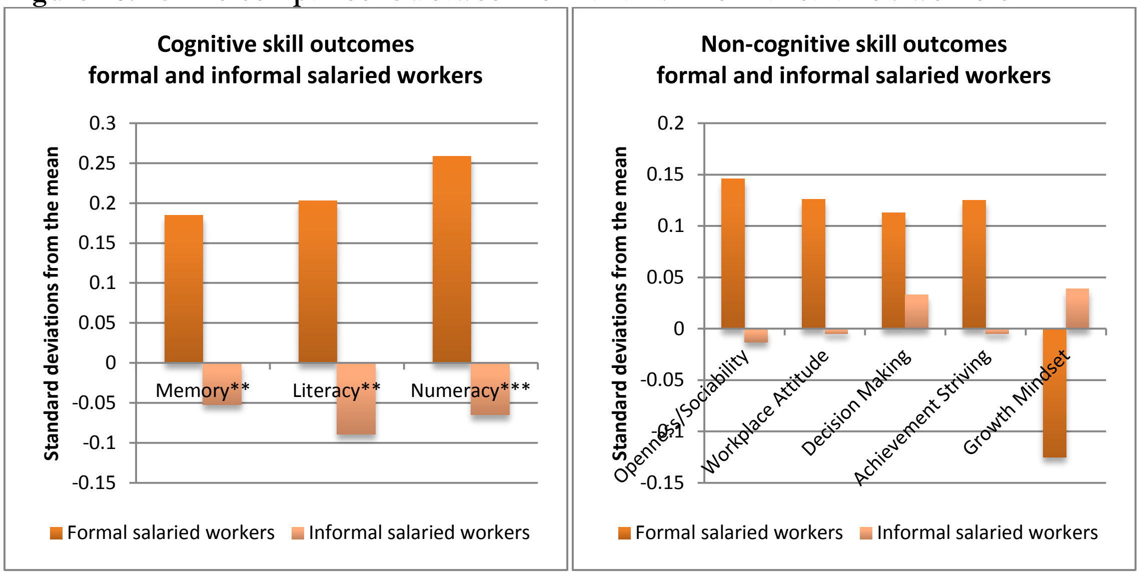
Figure 19: All cognitive skills and most non-cognitive skills are better among public and private sector employees relative to the self-employed



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.
Note: Respondents aged 25–64. F-test results are depicted by *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

And, finally salaried workers in the formal sector possess better cognitive skills than salaried workers in the informal sector. Consistent with the observation above, a higher skill set implies a higher chance of being in a formal sector job, typically jobs in the state administration or state owned enterprise (SOE), as well as in a medium or large privately owned company.

Figure 20: Skills comparisons between formal and informal salaried workers



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.
Note: Respondents aged 25–64. F-test results are depicted by *** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level.

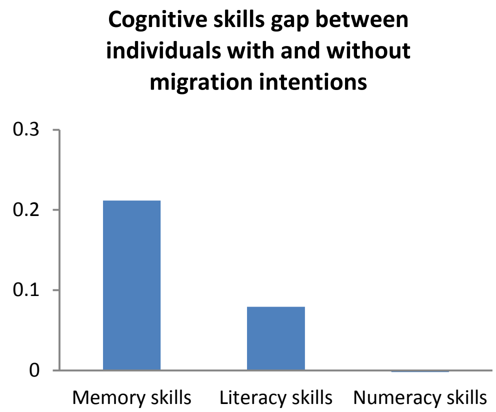
Box 4: Skills and migration in Uzbekistan and Kyrgyzstan

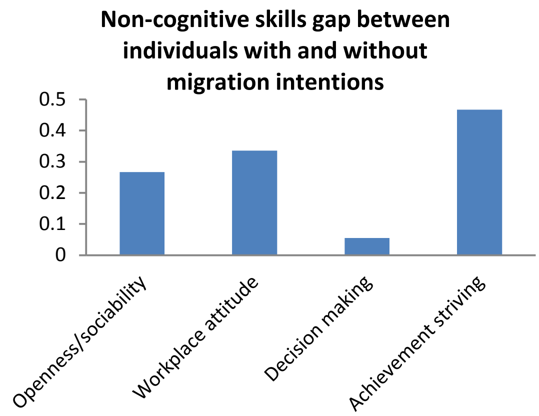
Existing studies find that migrants and non-migrants differ with respect to education and skills. Among the reasons are the selective migration of groups who can gain disproportionally from mobility (Borjas, 1987), investments in higher education for those who aspire to migrate (Mountford, 1997), or specific pre-migration investments in human capital (Danzer and Dietz, 2014). There is a broad range of literature on the self-selection of migrants with respect to formal educational attainments (e.g., Chiquiar and Hanson, 2005; Lanzona, 1998; Orrenius and Zavodny, 2005). However, evidence on the cognitive and non-cognitive skill endowment of migrants is scarce.

An analysis of adults with the intention to migration in the Kyrgyz Republic and Uzbekistan reveals that working age adults who plan to migrate typically possess above average cognitive and non-cognitive skills, compared to adults who have no migration plans (Figure 21). Note that this analysis cannot be conducted for each of the countries separately because the sample size is too small. For cognitive skills, the gap between working age adults who do and do not plan to migrate is sizeable for memory skills (greater than 20% of a standard deviation) and modest for literacy skills, but there is no difference for numeracy skills. For all measured non-cognitive skills, individuals with migration plans perform better than individuals without migration intentions; the gap is especially large with respect to achievement striving, reflecting the fact that migrating abroad implies a strongly positive contribution to family income in Central Asia. The finding that individuals who are planning to migrate, on average, have better cognitive and non-cognitive skills than others in the working-age population supports existing selection theories of migration. The results also suggest that studies focusing exclusively on education may draw very different conclusions.

Similarly, migrants who have returned after working abroad have significantly higher cognitive and non-cognitive skill outcomes than non-migrants (Figure 22). The gaps in cognitive skills between migrants who have returned and non-migrants are very large in absolute terms and much larger than the gaps seen between adults who intend to migrate and adults who do not plan to migrate. While this potentially implies learning effects through migration, it could also point to the fact that not all individuals who intend to migrate follow through and actually migrate. On the other hand, the skills gaps between migrants who return and non-migrants are lower than the gaps found between adults with the intention to migrate and working age adults with no migration intentions. The notable exception is decision making, in which migrants who return have high scores. Hence, while individuals who plan to migrate do not have much higher decision making skills, actual migrants have much higher decision making skills. This result could point either to the fact that adults with good decision making skills following through with their migration intentions, or that migrants learn such decision making skills while abroad. Disentangling these different possibilities remains for future research.

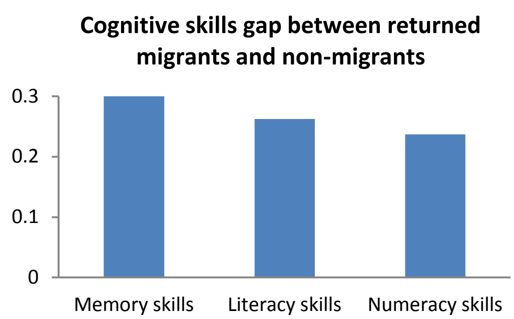
Figure 21: Adults with migration intentions on average have significantly higher cognitive and non-cognitive skills than adults without migration intentions, 2013

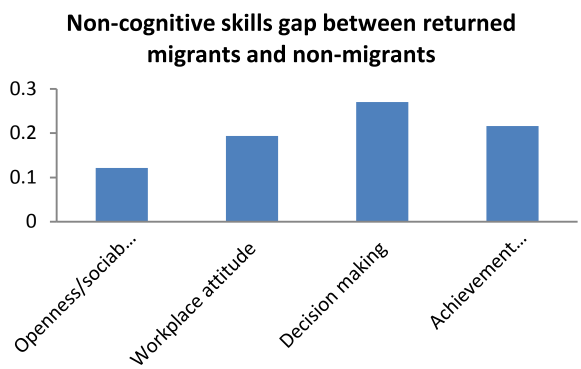




Source: Authors' estimates using World Bank/GIZ *Kyrgyz Republic and Uzbekistan Jobs, Skills, and Migration Survey,* 2013.

Figure 22: Returned migrants on average have significantly higher cognitive and non-cognitive skills than non-migrants, 2013



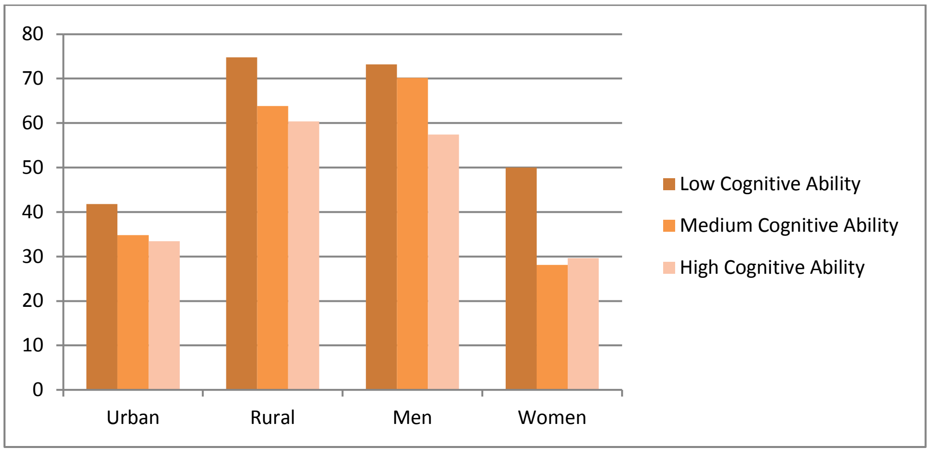


Source: Authors' estimates using World Bank/GIZ *Kyrgyz Republic and Uzbekistan Jobs, Skills, and Migration Survey,* 2013.

2.3 Workers with better skills use those skills more often in the workplace

Among the employed, individuals with higher cognitive skills are less likely to perform physically demanding work, although perhaps not by as much as one might expect. The difference in physical activity is particularly apparent for women, as 50 percent of women with low cognitive ability perform physical activities, as compared to less than 30 percent of women with medium or high cognitive ability (Figure 23). Among men with high cognitive ability, 57 percent engages in physically demanding work compared with 70 percent and 73 percent of medium, and low cognitive ability workers. Cognitive ability aside, physical work dominates in the rural areas.

Figure 23: Higher skilled workers are slightly less likely to perform physically demanding work

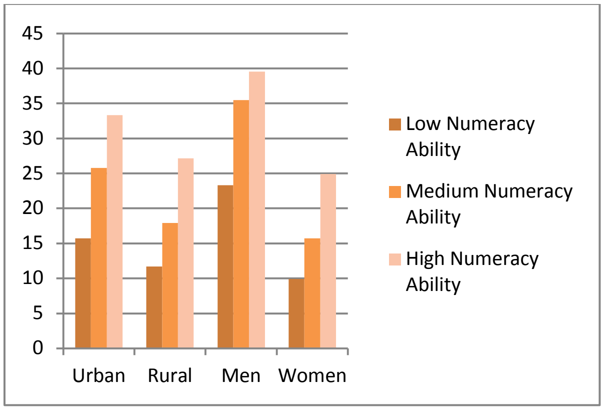


Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

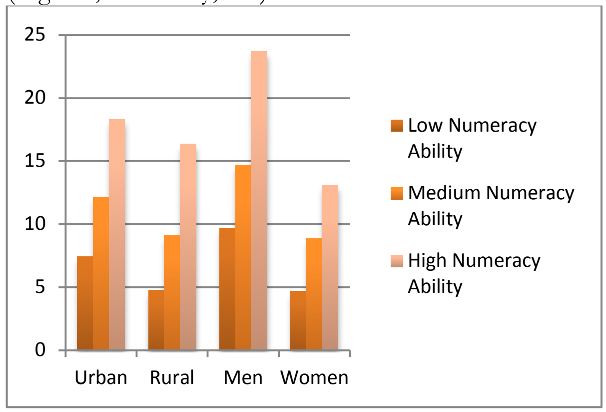
In addition, workers with higher cognitive skills tend to engage more in tasks requiring higher-level numeracy skills. Figure 24 shows that workers with high numeracy ability are more likely to be using numeracy in tasks on the job. Workers with high numeracy ability are twice as likely, on average, to calculate fractions, decimals or percentages as individuals with lower numeracy skills. Meanwhile, individuals with higher cognitive skills are almost three times more likely to use advanced numeracy skills on the job than their counterparts with lower cognitive skills. These differences hold in urban and rural settings, and between men and women.

Figure 24: Workers with high numeracy ability are more likely to use numeracy on the job

Respondents using numeracy skills on the job



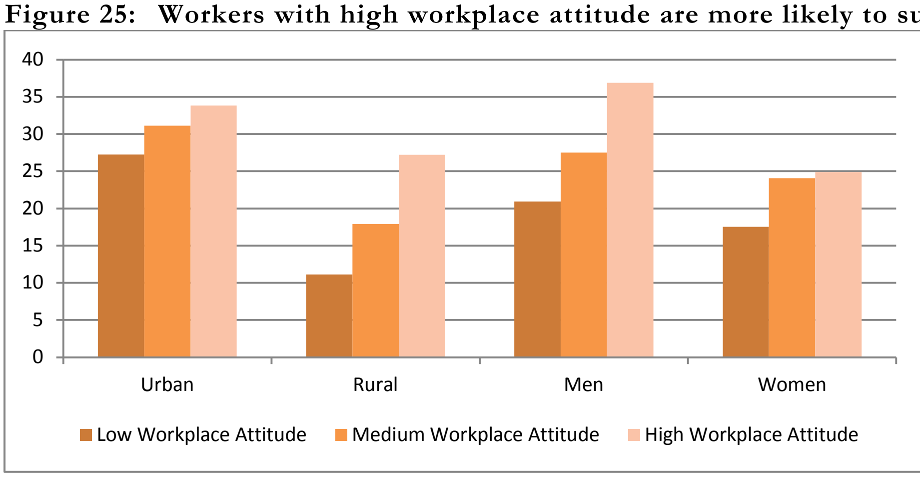
Respondents using advanced numeracy skills on the job (Algebra, Geometry, etc.)



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Workers with higher non-cognitive skills are also more likely to supervise others' work. Workplace attitude is a compilation of traits including having ideas others have not previously thought of; working very hard; and enjoying working on things that take a long time to complete. Individuals with high workplace attitude are more likely to supervise the work of others than those with low or medium workplace attitude (Figure 25). This is particularly the case in rural areas and for men. Being more open and sociable also increases the likelihood of having contact with people beyond one's colleagues, such as clients, customers, or students, allowing workers to increase their professional network.

Figure 25: Workers with high workplace attitude are more likely to supervise others

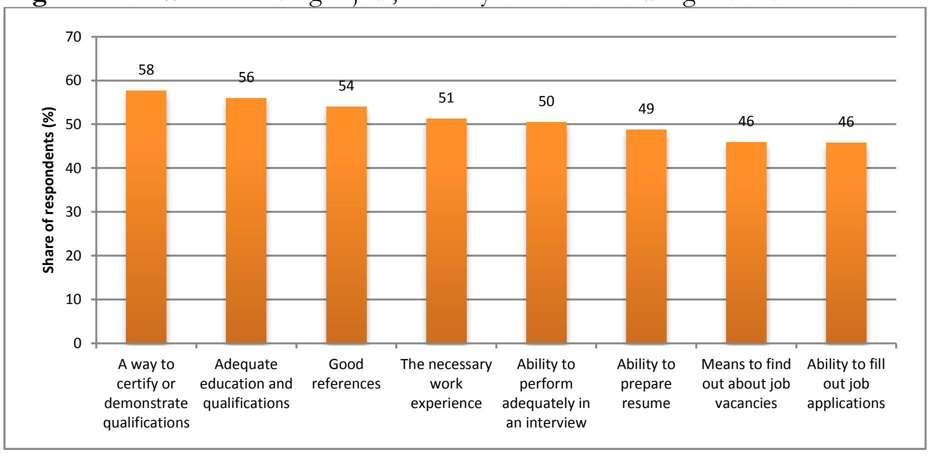


Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

2.4 There are deficiencies in the job search and skill signaling process

In sum, greater cognitive and non-cognitive skills correlate with better employment outcomes. Still, respondent feedback suggests there is still considerable scope for improvement. Specifically, deficiencies in job search methods and skill signaling among workers can also play an important role in explaining skill mismatches. Only about 40 percent of respondents report that they are able to certify or demonstrate their qualifications to an employer, or have initial adequate qualifications (Figure 26). This aligns with findings that workers' qualifications are moderately applicable within the current labor market. Moreover, almost half of respondents report significant barriers to learning about vacancies—an integral component to matching labor supply and labor demand.[17] Almost half of respondents do not believe they have the means to learn about job vacancies. And if they did, almost half feel unprepared to prepare a resume, perform in an interview, or provide good recommendations.

Figure 26: When finding a job, are any of the following a constraint?



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

[17] Qualitative studies suggest that young people and urban population have access to job postings on the internet, which is not the case for the rural population where access to the Internet is limited (World Bank, 2013b).

3 Skill Formation

This section first summarizes the literature on skills development and addresses a fundamental question for the Kyrgyz Republic: does the education and training system impart the cognitive and non-cognitive skills needed to successfully participate in the labor market?

3.1 Skills are formed throughout the life cycle

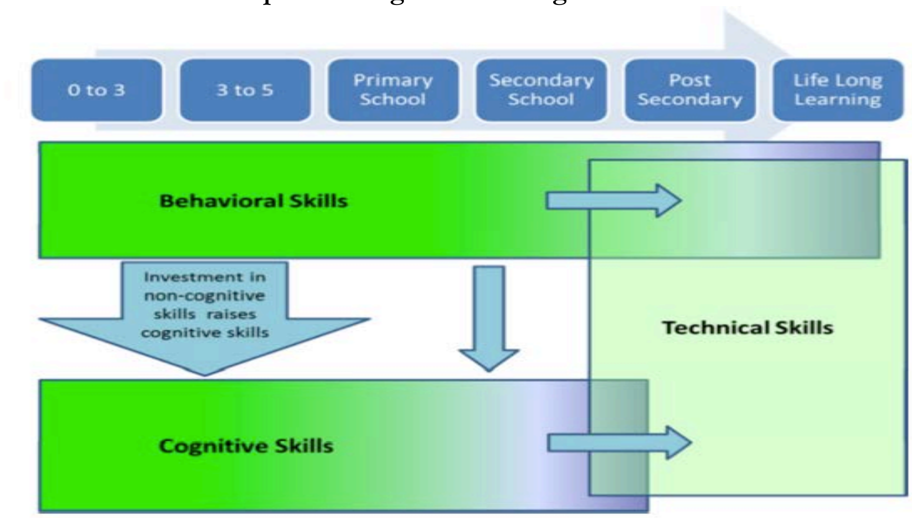
Skills are developed throughout all stages of life—from conception to preschool, primary, secondary, higher education, and on the job—and there are sensitive and critical development periods for each type of skill. Recent evidence suggests that the most sensitive and critical moments for skill building differ by skill type; these "malleable" periods are depicted in green in Figure 27. Cognitive and non-cognitive skills are largely formed earlier on in life, while technical skills are developed later.

The early childhood period is critical in the development of cognitive skills. This stage marks the first step of skill-building, and it can be particularly critical in closing the gap between children from poorer and better-off households. In fact, there are strong indications that the most critical moment for cognitive skill-building is before a child turns 5. By ages 8 to 10, the foundation of an individual's cognitive abilities is well set. Technical skills are developed later—they are continuously developed throughout adolescence and into adulthood.[18]

Developing strong cognitive and non-cognitive skills early in the life cycle is imperative for building the skills needed for productive employment later in the life cycle. Strong cognitive and non-cognitive skills feed into the successful acquisition of technical skills, as solid cognitive and non-cognitive foundations will help workers to strengthen their technical skills throughout their working lives.[19] These skills also shape the capacity and motivation to absorb new knowledge, adapt, and solve new problems, thus affecting one's ability to learn across the life cycle. Such skills are crucial in a dynamic economy where specific skills can be rendered obsolete. This is not to say that generic skills, particularly non-cognitive skills, are an alternative to academic qualifications. Instead, careful attention to these skills is a powerful way to enhance educational attainment, life-long learning, and employability.[20]

[18] Heckman and Cunha (2010); Heckman (2000, 2006).
[19] World Bank (2013d).
[20] Arias et al. (2014).

Figure 27: Skills are developed throughout all stages of life



Source: World Bank (2013d).

3.2 Educational attainment rates are high, but the Kyrgyz Republic is missing important opportunities for skill development at various stages of the life cycle

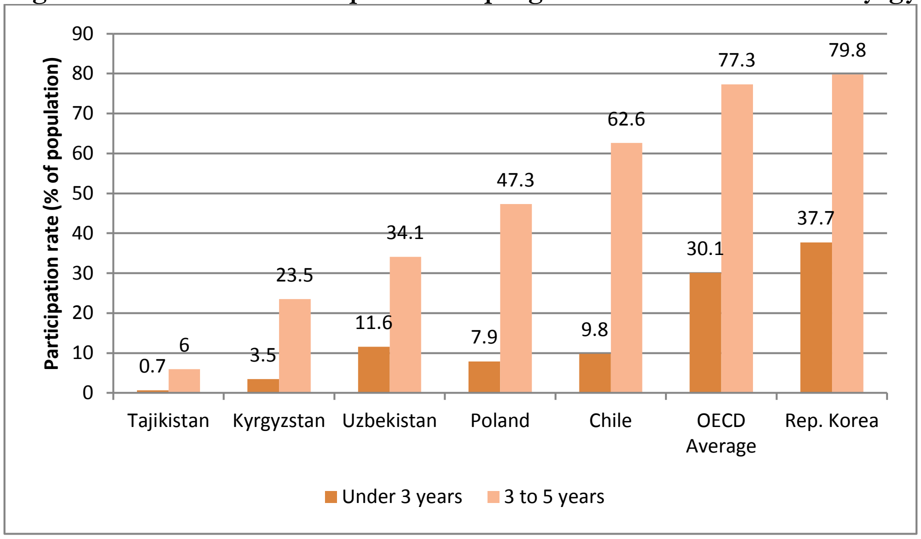
Research shows that investing in children early can be the most cost-effective way to impart skills that contribute to higher productivity later in life. The consequences of underinvestment in early childhood development (ECD) are serious. Not only does early education help to build the foundation for learning skills throughout life, but early childhood education is an important element in ensuring that youth have an adequate amount of schooling to prepare them to enter the labor market. Early childhood development includes not only the teaching of developmental skills to children, but also proper health care and nutrition.

The Kyrgyz Republic is investing in early childhood development through efforts to support appropriate dietary consumption for pregnant women and children. Iron and folic acid deficiencies plague many children in the region. The Government has sought to combat this with laws on salt iodization and flour enrichment. The Ministry of Health has developed a nutrition strategy that emphasizes interventions targeted for young children and pregnant women.[21]

In addition, the Kyrgyz Republic passed a Law on Preschool Education in 2009, and investment in early childhood education has increased in the last five years. However, at 24 percent, net enrolment rates for children aged 3–5 remain low (Figure 28), and are well below the OECD average of 77 percent. Similarly, enrollment among children under 3 years old is also well below the OECD average. Qualitative studies suggest a lack of available pre-school facilities in the country. Those that are operational either have no space to meet the demand or are too expensive for the general population.[22] Thus, one mechanism for addressing the skill formation of future workers is to continue to create an enabling environment for early childhood education and ensure access and quality to this education.

[21] World Bank (2013a).
[22] World Bank (2013b).

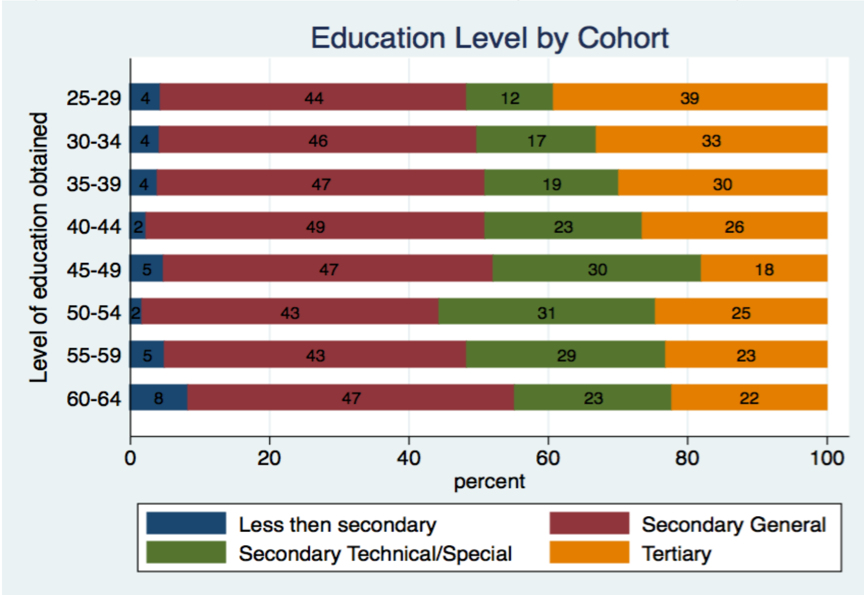
Figure 28: Enrollment in preschool programs is still low in the Kyrgyz Republic, 2013



Source: Authors' estimates using the World Bank/GIZ *Jobs, Skills, and Migration Survey,* 2013, OECD (2013).

The next stage in skill formation is the formal education system. Overall, education completion rates are high in Kyrgyz Republic. Only four percent of the population aged 25–29 has failed to complete at least secondary general. Tertiary completion rates are 27 percent for the working age population. The overall tertiary completion rate is higher than in OECD countries, where 23 percent of the working age population has completed tertiary education. Tertiary education completion rates have continuously risen over the past 20 years, with various private institutions offering short practical programs. As many as 39 percent of 25- to 29-year-olds have completed tertiary education. Finally, for individuals younger than 45, women are likely to have a higher education level than men. For 25- to 29-year-olds, 56 percent of women have completed secondary technical or university, while only 46 percent of men possess the same credentials. In addition to the results presented, Appendix D: Summary Tables contains more detailed results on educational attainment in Tajikistan among the working age population.

Figure 29: Education completion is high, with tertiary graduates expanding



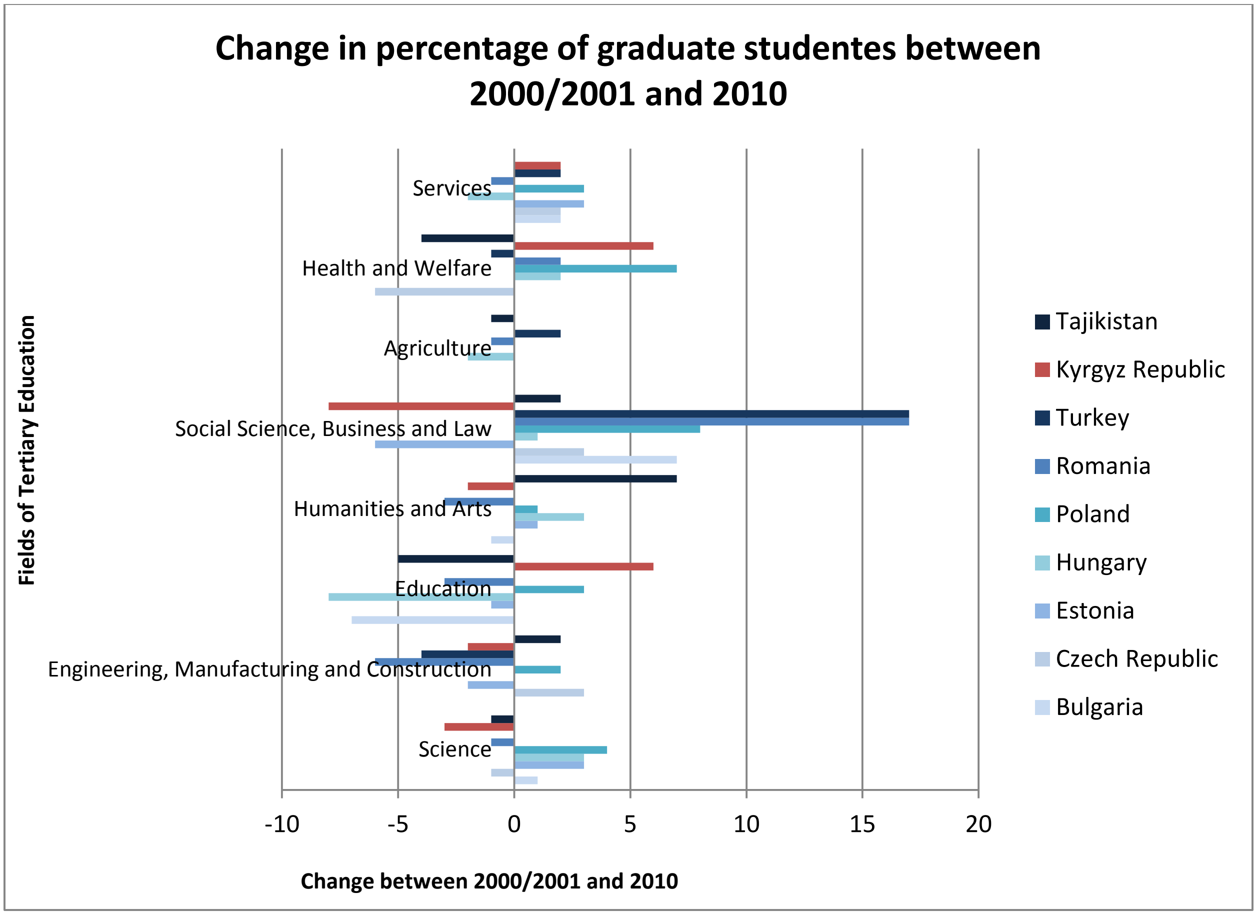
Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Changes in fields of study in tertiary education may illustrate some degree of the mismatch between skills and the labor market. Figure 30 illustrates changes in fields of study between 2000 and 2010. In the Kyrgyz Republic, more students chose to study services, health and welfare, and education in 2010 than in 2000. On the other hand, fewer students opted to study social sciences, business, law, humanities, arts, engineering, manufacturing and construction. Students are opting out of precisely those fields that require higher-level skills, and which have an increased demand in the labor market of more modern economies. In particular, professionals in science, technology, engineering and mathematics are considered critical to the development of knowledge-intensive industries, but fewer students are choosing these fields in the Kyrgyz Republic.[23] The change in fields of study may be related to the phenomenon whereby more and more students opting for tertiary education as a means to postpone labor market entry.[24]

[23] Arias et al. (2014).

[24] Helemäe and Saar (2000); ILO (1999); Róbert (2003).

Figure 30: More Kyrgyz students are studying health, education, and services in tertiary fields—2000 to 2010



Source: Arias et al. (2014); World Bank estimates based on UNESCO Education Digest (2003, 2012).

Furthermore, the rise in tertiary education has been accompanied by a decline in secondary vocational training. While consistent with the shift in the labor market toward the service sector, this may limit industrial expansion. Many post-soviet countries experienced declines in production facilities after transition, and the Kyrgyz vocational system lost its formal connection to the workplace. Professions offered in vocational training are specialties that employers continue to recognize, but standards and equipment have deteriorated. This deterioration has led to antiquated and low-quality content and an overall demise of the vocational track.[25] While the agency responsible for vocational education and training has worked for many years to improve employer involvement in vocational schools, their efforts are not widely considered successful. Nonetheless, the analysis above showed that graduates from secondary technical/special institutions do tend to have better labor market outcomes than those completing secondary general: women are more likely to work, and both men and women with secondary technical/special are more likely to be in formal sector jobs. Also note that in many countries, vocation graduates have employment gains at youth, but those gains may be offset at older ages due to less adaptability and difficulties transitioning between jobs.[26] As a result, there are

[25] Baumann et al. (2013).

[26] Arias et al. (2014).

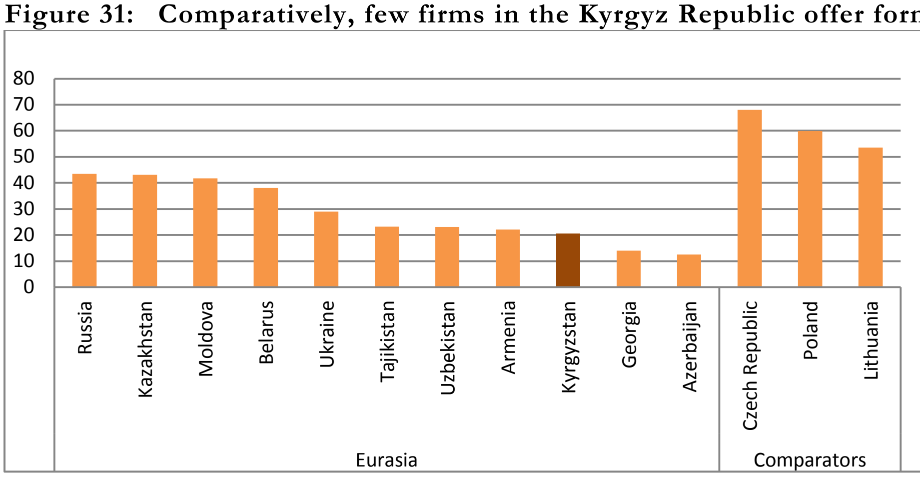
many instances in which vocational education can remain a small part of an educational system, while the emphasis can be on more adaptable skill development.

In 2012 the Kyrgyz Republic embarked on an ambitious education development strategy (EDS 2020). The strategy is the first in the Kyrgyz Republic to include both general education and vocational education, and sets development priorities. EDS 2020 focuses on quality, access, and inclusion. In addition, the strategy focuses on the relevance of education to the labor market and employer interaction.[27]

While the education system is traditionally relied upon to develop skills required for the labor market, skills are also built outside of the formal system. Just as early education helps build skills before formal education begins, professional education continues skill formation after formal education ends. After students leave the formal system, on-the-job education and training can ensure that the workforce maintains adequate skills in a rapidly changing economy. Ensuring adequate access to quality professional education is crucial for meeting the skill needs of an expanding and rapidly changing economy. A significant portion of this learning takes place as an adult in post-formal education. This includes skills acquired by performing specific tasks at work and receiving on-the-job training. In the United States, it is estimated that on-the-job training contributes approximately a quarter to half of all human capital.[28] Adult education and training also increases worker productivity. A 2004 OECD study shows that employee training impacts the wage growth of both young and highly educated employees.

Despite international evidence on the importance of post-formal education, few firms in the Kyrgyz Republic offer formal training programs to full-time employees. Comparatively, Kyrgyz firms tend to underinvest in their own employees, possibly as a result of market failures that dissuade such investments. Indeed, only about 20 percent of all Kyrgyz firms offer their full-time employees formal training programs. In comparison, almost 70 percent of Czech firms and 60 percent of Polish firms offer formal training to their full-time employees (Figure 31). Kyrgyz firms fall significantly below the proportion of firms offering training in Eastern Europe and neighboring countries.

Figure 31: Comparatively, few firms in the Kyrgyz Republic offer formal training



Source: Gill et al. 2014 based on the EBRD-World Bank Business Environment and Enterprise Performance Surveys (BEEPS) (2009).

[27] European Training Foundation (2013).
[28] Heckman et al. (1998).

3.3 Cognitive skill outcomes and educational attainment are correlated, but wide variations exist within education levels

International PISA results capture cognitive skills of the new generation of labor market entrants, and as such act as a measure for the quality of education today. OECD PISA tests directly capture the reading, math, and science abilities of 15 year olds, or cognitive abilities. Recent evidence shows that the tests also capture differences in motivation, attention and persistence, or non-cognitive skills.[29] Such assessments are critical in making informed policy and management decisions about learning and labor market outcomes. PISA participation has led a number of countries to realize that their education systems are greatly in need of reform and it has prompted reforms. While there are several examples, Germany and Poland are good examples of countries that were spurred by weak PISA results to reform their education systems and thereby improve their PISA performance.

Kyrgyz Republic was one of the few CIS countries to participate in PISA in 2006 and 2009. Scores improved between the two testing periods in all three categories, but remained low. Even in 2009, 83 percent of students still tested at or below the threshold for functional literacy. Thus, 83 percent of students were unable to read and draw useful information from a simple text. In addition, 81.9 percent scored at or below basic proficiency in science, and 86.6 percent scored at or below basic proficiency in math. Thus, the majority of students did not reach the lowest level of foundation skills and remain without a minimum level of skills to succeed in the knowledge economy.

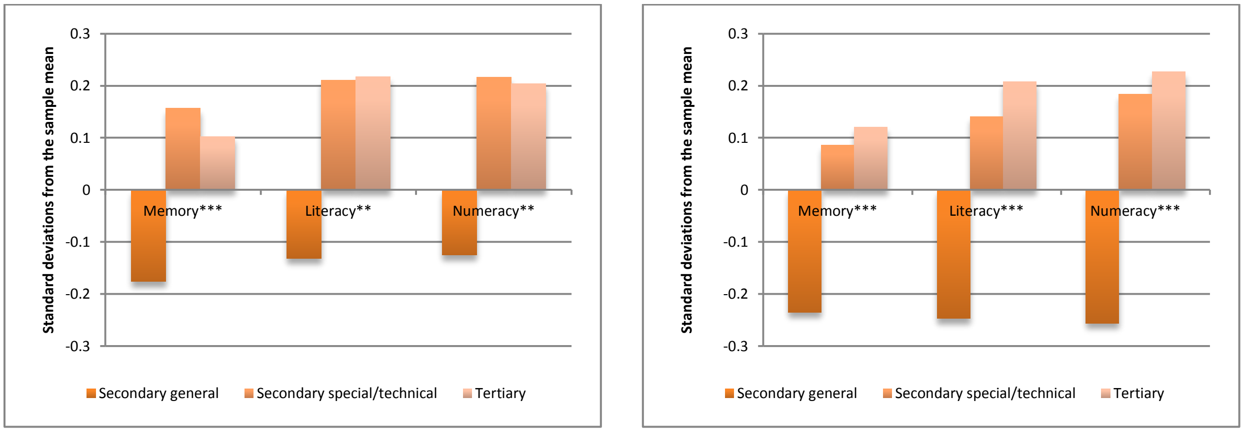
Among adults, tertiary and secondary technical/special graduates display significantly higher cognitive abilities than secondary general graduates, although there is considerable overlap across education levels. While cognitive ability increases with education (Figure 32), heterogeneity is high within education categories. A significant number of higher education graduates have lower or equivalent cognitive ability as individuals with a general secondary education, and vice versa (Figure 33). The commonalities between education levels suggest that issues with education quality may exist.

[29] Borghans et al. (2008).

Figure 32: Cognitive skills are correlated with educational attainment for both men and women

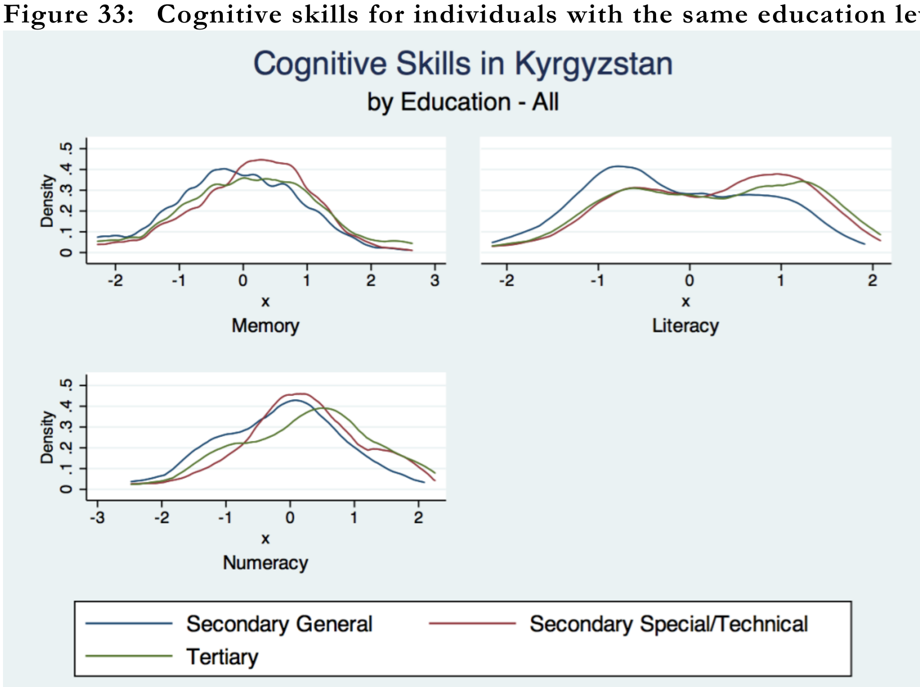
Cognitive Skill Mean Scores, by Educational Attainment - Men

Cognitive Skill Mean Scores, by Educational Attainment - Women



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.
Note: ***significant at 1% level.

Figure 33: Cognitive skills for individuals with the same education level vary dramatically



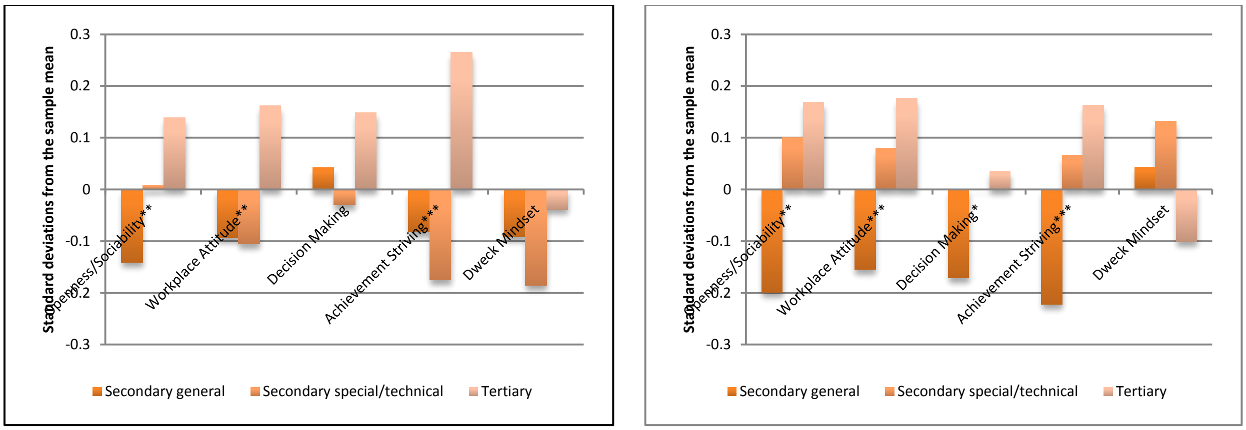
Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Tertiary graduates also have higher non-cognitive skills than secondary general and technical/special graduates, but here too there is considerable overlap across education levels. While individuals with a secondary vocational education scored relatively similar to individuals with a tertiary education on cognitive skills, individuals with a tertiary education appear to have significantly higher non-cognitive skills. These results are more pronounced for men than women (Figure 34). However, as with cognitive skills, there is a large degree of variation in non-cognitive skills among individuals with the same education levels. In fact, some higher education graduates displayed lower non-cognitive ability than individuals with general secondary education, and vice versa (Figure 35).

Figure 34: Non-cognitive skills are significantly better in tertiary educated individuals

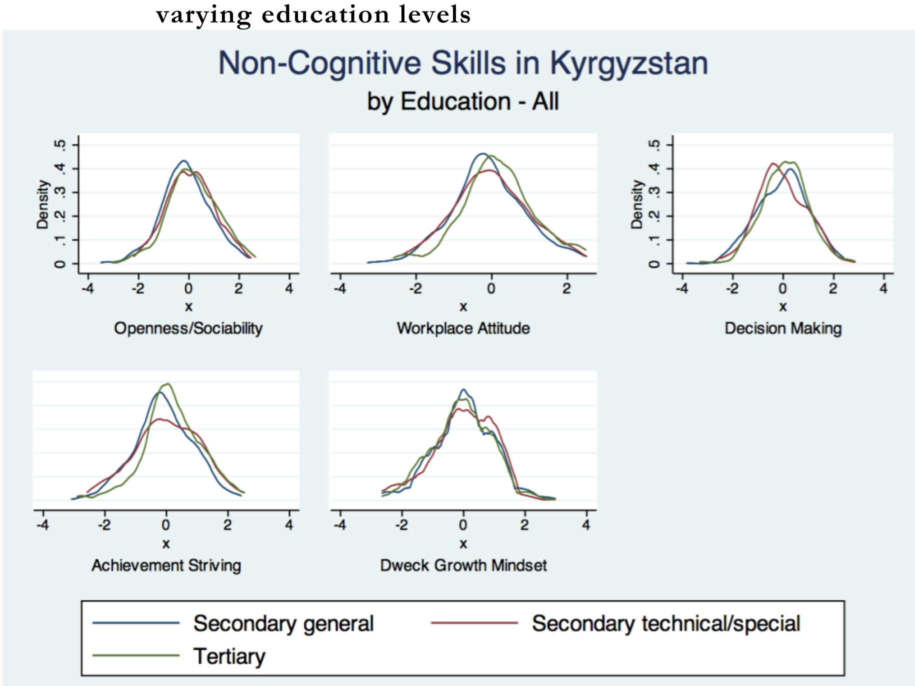
Non-cognitive Skill Mean Scores, by Educational Attainment - Men

Non-cognitive Skill Mean Scores, by Educational Attainment - Women



Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.
Note: ***significant at 1% level; ** significant at 5% level; * significant at 10% level.

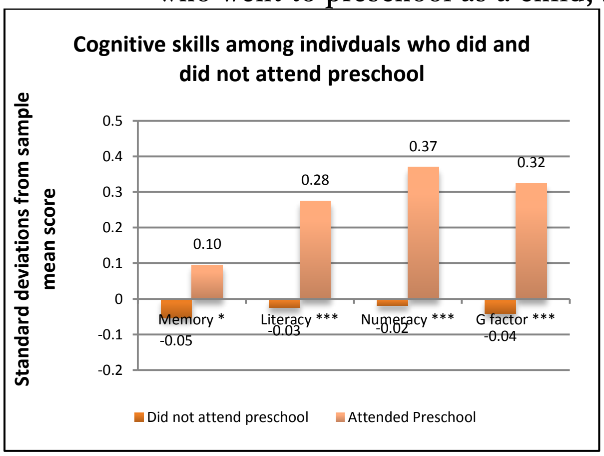
Figure 35: There is a considerable degree of overlap in non-cognitive skills for individuals of varying education levels

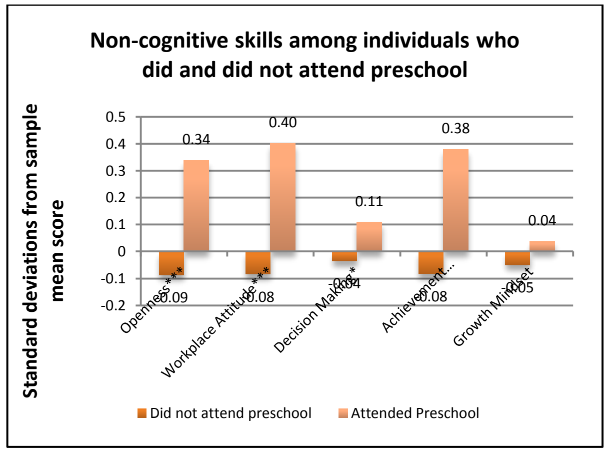


Source: World Bank/GIZ *Kyrgyz Republic Jobs, Skills, and Migration Survey,* 2013.

Having attended an early childhood education program in the Kyrgyz Republic is significantly correlated with cognitive skills later in life, even after controlling for educational attainment. Adults that have completed at least one year in preschool as a child on average do significantly better on both cognitive skill tests (including memory, literacy, and numeracy) and non-cognitive skills (such as openness, workplace attitude, and achievement striving) than adults who did not go to preschool. When demographic characteristics such as age, gender, marital status, area, and (most importantly) educational attainment are taken into account, having attended preschool as a child remains a significant correlate of cognitive ability and in particular numeracy skills and, to a lesser extent, literacy skills. Non-cognitive skills are also robust to controlling for such background characteristics, openness, workplace attitude and achievement striving in particular (Figure 36).

Figure 36: Both cognitive and non-cognitive skill outcomes are significantly better in adults who went to preschool as a child, 2013



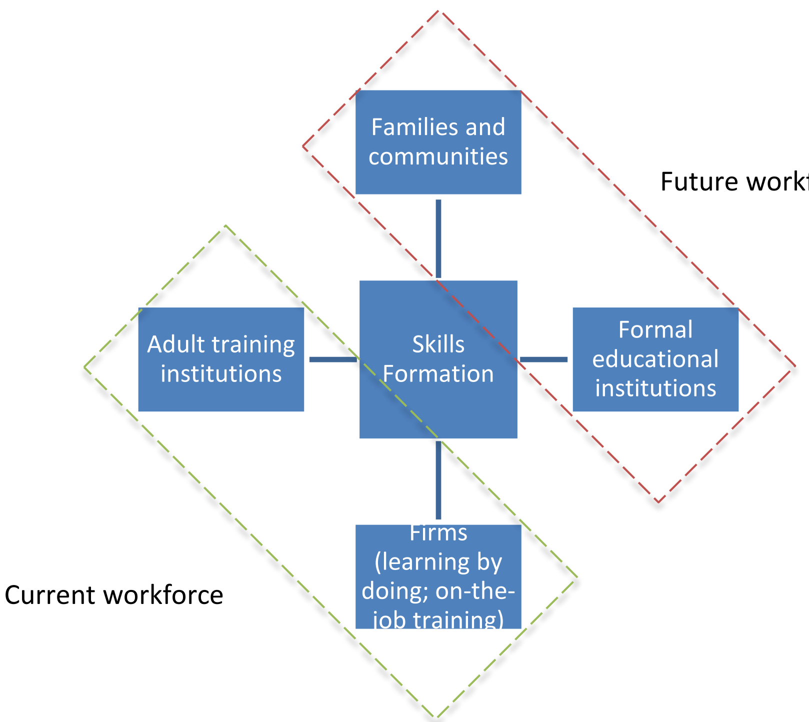


Source: Authors' estimates using World Bank/GIZ *Kyrgyzstan Jobs, Skills, and Migration Survey,* 2013.
Notes: Respondents aged 25–64; ***/**/* represent significant differences in outcome between individuals with and without preschool at the 1%/5%/10% significance level, respectively.

4 The Skills Roadmap in the Kyrgyz Republic

The Kyrgyz economy is changing and with it the demands for skills. The service sector has been growing fast and the industrial sector has also started to grow. These structural changes, as well as the Kyrgyz aspiration more broadly to become a middle income country, require a different, more diverse skill set of the labor force, which includes non-cognitive skills alongside high quality cognitive and technical skills. Policies can target the future workforce, usually by focusing on families and communities and the formal education system, and/or the current workforce, by focusing on adult training institutions and on-the-job training by firms (Figure 37).

Figure 37: Actors that play a role to build skills throughout the life cycle of an individual



Source: Authors' illustration based on Heckman (2000).

The development of skills policies can be informed by the Skills Toward Employment and Productivity (STEP) Framework (see Box 5). The STEP Framework contains five steps to improve employability and productivity in a country: (1) getting children off to the right start; (2) ensuring that all students learn; (3) building job-relevant skills that employers demand; (4) encouraging entrepreneurship and innovation; and (5) matching the supply of skills with employer demand. These steps apply to all countries, with the degree of emphasis varying depending on the government's strategic vision, which in turn is constrained by budget and capacity constraints.

Box 5: The STEP Framework

The following is a summary of the STEP conceptual framework which brings together research-based evidence and practical experience from diverse areas

Step 1. *Getting children off to the right start:* by developing the technical, cognitive, and non-cognitive skills conducive to high productivity and flexibility in the work environment through early child education (ECE), with an emphasis on nutrition, stimulation, and basic cognitive skills. Research shows that handicaps developed early in life are difficult if not impossible to remedy later and that effective ECE programs can have a very high payoff.

Step 2. *Ensuring that all students learn:* by building stronger education systems with clear learning standards, good teachers, adequate resources, and a proper regulatory environment. Lessons from research and on-the-ground experience indicate that the key decisions about education systems are how much autonomy to allow and to whom, how much accountability to expect from whom and for what, and how to assess performance and results.

Step 3. *Building job-relevant skills that employers demand*: by developing the right incentive framework for both pre-employment and on-the-job training programs and institutions (including higher education). A growing body of experience is showing how public and private efforts can be combined to achieve more relevant and responsive training systems.

Step 4. *Encouraging entrepreneurship and innovation*: by creating an environment that encourages investments in knowledge and creativity. Emerging evidence shows this requires innovation-specific skills (which can be developed starting early in life) and investments to connect people with ideas (such as through collaborations between universities and private companies) as well as risk-management tools that facilitate innovation.

Step 5. *Matching the supply of skills with employer demand*: by moving toward more flexible, efficient, and secure labor markets. Avoiding rigid job protection regulations while strengthening income protection systems, complemented by efforts to provide information and intermediation services to workers and firms, make up the final complementary step that enables skills to be transformed into actual employment and productivity.

Source: Valerio et al. (2014).

Within the STEP framework, the findings in this report point to several priority areas of public policies that can strengthen the quality, relevance, and use of skills over the life-cycle:

1. *To get children off to the right start* by continuing to emphasize public policies that seek faster universal access to early childhood development services, building on the nutrition and preschool strategies, and the recent findings from the institutional SABER ECD review[30] (see Appendix F: SABER ECD 2013—Summary of policy options to improve ECD in the Kyrgyz Republic). These efforts should be promoted as an integral part of a strategy to build strong skills for the future.

2. *Ensuring that all students learn* and *build job-relevant skills that employers demand* by building on public policies, such as the education development strategy (EDS 2020), that:

    - Seek to build strong non-cognitive skills at all education levels, alongside strong cognitive skills. Non-cognitive skills are already important in today's labor market and are likely to

[30] http://wbgfiles.worldbank.org/documents/hdn/ed/saber/supporting_doc/CountryReports/ECD/SABER_ECD_Kyrgyz_Republic_CR_Final_2013R.pdf.

become more important for tomorrow's labor market. Given the low secondary general performance, a particular focus on strengthening secondary general education is particularly important.

- Promote non-cognitive skill building in schools. An increasing number of countries worldwide have implemented national legislation to promote non-cognitive skill building in schools, including Australia, Colombia, Romania, Spain, and the United Kingdom[31], and are integrating non-cognitive learning into the regular school curriculum by training teachers, adopting a structured curriculum, evaluating students, and investing in efforts to improve the school climate. Schools provide an ideal environment for early cognitive and non-cognitive skills development, given that children are typically in a single classroom with a single teacher and the same group of peers for an entire school year. This "single point of entry" reduces the costs of interventions and increases the likelihood of a positive impact on skills development.

- Emphasize systematic measurement of skills alongside education and labor market outcomes. For example, carrying out national and international student assessments can help to inform policy makers about the quality of secondary general education for preparing students for the labor market.

- Encourage more students to invest in technical/science training, both at the secondary and tertiary level. This may also include demand-side policies that aim to improve basic information on labor market outcomes for graduates of different degrees and specializations (and thus also fall under STEP point 5: *matching the supply of skills with employer demand*), and supply-side policies that aim to make these types of technical/science trainings more accessible/attractive.

3. E*ncouraging entrepreneurship and innovation* by emphasizing public policies that:

   - Encourage firms to enhance skills use and skills investments. Building job-relevant skills will require a multi-pronged effort that includes: (i) addressing the technical or job-specific skills gaps by implementing labor market programs; and (ii) addressing market failures that prevent firms from providing on-the-job training (OJT) and incentivizing firms to provide OJT.

   - Support migrants to build more skills to increase their earning capacity and therefore their ability to support their families. To do so, policy makers can introduce pre-departure training programs for migrants to ensure that they have the basic language skills and knowledge of social services provision and migrant protection programs. The Philippines, for example, carries out pre-departure reviews and approvals of contract terms, in addition to providing a mandatory pre-departure orientation. Better prepared migrants can find better quality jobs that build more skills and provide greater earnings, which can boost remittances and boost skills levels of return migrants.

[31] Arias et al. (2014).

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Appendix A: Questionnaire Sections

Visit 1: (All) Household Members	Visit 2: Selected Household Member
1. Demographic Profile Card	1. Labor Conditions
2. Education	2. Labor Market Expectations
3. Education Expenditure	3. Russian Language Skills
4. Immigration	4. Return Migrants Pre-Departure Preparation
5. Employment	5. Future Migrants' Pre-Departure Preparation
6. Labor Market	6. Pre-Departure Questions about Skills Acquisition for Future Migrants and Return Migrants
7. Work Migration Cycle	7. Most Recent Technical Skill Training
8. Most Recent Migration Event	8. Technical Skills: Reading and Writing
9. Remittances/Gifts from Non Household Member	9. Workplace Skills
10. Migration Intent	10. Non-Cognitive Skills: Part A
11. Health Expenditure	11. Non-Cognitive Skills: Part B
12. Financial Services	12. Cognitive Skills: Memory
13. Subjective Poverty	13. Cognitive Skills: Language
14. Habits And Adaptation	14. Cognitive Skills: Text Comprehension A
15. Food Consumption	15. Cognitive Skills: Text Comprehension B
16. Non-Food Consumption	16. Cognitive Skills: Table Comprehension
17. Other Non-Food Consumption	17. Cognitive Skills: Publicity Comprehension
18. Large Items of Non-Food Consumption	18. Cognitive Skills: Graph Comprehension
19. Fuel	
20. Payment for Utilities and Electricity	
21. Dwelling	
22. Energy	
23. Availability of Utility Equipment	
24. Gifts	
25. Government Transfers	
26. Subjective Budget—Remittances	
27. Selection Of Member For Follow Up Survey	

Appendix B: Constructing Cognitive Skills Scores Methods for Scale Development and Scoring

Prepared by Carly Tubbs, Ph.D. Candidate, New York University; Louise M. Bahry, Ph.D. Candidate, University of Massachusetts Amherst; Robin Audy, World Bank.

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:

(1) *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). Researchers in developmental psychology and elsewhere propose that such skills are important for school readiness and labor force attainment since they enable individuals to regulate cognitive and emotional responses that in turn allow individuals to engage more effectively in learning activities (Fuchs et al., 2005). We assessed one component of executive functioning—working memory—using a 12-item memory scale adopted from the Skills and Labor Market Survey (ENHAB)[32]. These items tested the short-term recall of increasingly longer number sequences (starting with two numbers and ending with 9 numbers). Enumerators gave respondents three practice examples with two-number sequences to train the respondents on how to answer the questions, and were instructed to read out numbers at a regular pace to avoid grouping.

(2) *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). In this study, we assessed various concepts within the domains of literacy and numeracy using multiple-choice questions with four answer choices. Within literacy, these concepts include: (1) *semantics*, assessed using seven items, with five items assessing respondents' familiarity with vocabulary, one item testing understanding of a national idiom, and one item measuring comprehension of the meaning of a complex sentence;[33] (2) *reading comprehension*, assessed by asking respondents to read a 257-word non-technical narrative text and then answering five questions about the text; and (3) *information comprehension,* assessed using four items based on instructions for taking a medicine and reading a timetable describing inter-city bus schedules. Within numeracy, concepts include: (1) *arithmetic*, assessed using three questions about prices in an advertisement; and (2) *graph comprehension*, assessed using three questions based on a graph of Bulgaria's population growth from 1900 to 2011. The items assessing reading comprehension and semantics were taken from existing instruments fielded by the World Bank with Bulgarian students, while the items assessing mathematics and information comprehension were adapted from the Adult Literacy and Lifeskills Survey (Murray, Clermont, & Binkley, 2005).

[32] The ENHAB is a recent survey in Peru which gathers data on cognitive and socio-emotional test scores, individual's characteristics, educational trajectory, and wages.

[33] An issue with translation of the items comprising the semantics scale rendered the data from this set of items unusable. The semantics scale was thus not considered for analysis, leaving the total number of assessed skills at five.

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).

Analysis Strategy

All missing values were recoded as incorrect answers, resulting in a set of 33 dichotomous or binary items.[34] 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 (for more information, see Box C1, "What is Factor Analysis and Why do We Use It?" in Appendix C). Refined scoring methods that account for measurement error include the production of factor scores using factor analysis or item response theory (IRT) methods.

Box B1: What is Item Response Theory and When Can We Use It?

Item Response Theory (IRT) is an approach, or family of statistical models, used to analyze assessment item data, such as cognitive skills assessment data. Several IRT models have been developed to estimate ability or person parameters that are scored either dichotomously (i.e. only two response categories) or polytomously (i.e. more than two response categories; Hambleton, Swaminathan, & Rogers, 1991). Traditionally, IRT has been used for educational applications for Computerized Adaptive Testing (CAT), test score equating, item analysis, and test banking. However, due to the advantages of IRT, other disciplines have recently developed an interest in using IRT for scoring, validation, and other psychometric analyses (Reise & Henson, 2003).

There are two over-arching families of item response models which differ greatly in theoretical and mathematical background and analysis. The first of the two families, the logistic models, relate examinee ability (θ) and item parameters using logistic functions. The logistic family of IRT models allow for the estimation of up to three item parameters, or characteristics. The one-parameter (1PL) model is the most basic and involves, as the name states, only one item parameter: the b-parameter is included in every IRT model and is considered the difficulty parameter (Yen & Fitzpatrick, 2006). The b-parameter is at the point on the θ scale where the probability of a correct response is equal to 0.50 and typically varies from -2.00 to 2.00 (Hambleton et al., 1991; Yen & Fitzpatick, 2006), increasing as items become more difficult. The two-parameter model (2PL) includes a second item parameter, the discrimination parameter, a. a is the slope of the item characteristic curve (ICC) at the point of inflection and the higher the value of a, the more sharp the discrimination (Yen & Fitzpatrick, 2006). Finally, the three-parameter model (3PL) includes the c-parameter, called the guessing or pseudo-chance parameter. This parameter was introduced to account for the possibility

[34] 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.

that even students with low ability have some chance of answering even difficult questions correctly. This parameter is not always necessary, and if set to zero, equates the 3PL with the 2PL (Yen & Fitzpatrick, 2006).

One of the big advantages of using IRT is that the ability or person parameters (θ) are not item or test dependent, and item and test characteristics are not dependent on the ability or person parameters. This is called the *property of invariance* (Hambleton et al., 1991; Lord, 1980). It means that the test and item parameters remain the same regardless of the sample of respondents, and the ability or person parameters do not vary depending on the test items administered or the time of test, provided the items are relevant to and representative of the same domain of interest.

Although there are clear benefits to the invariance property, there are two integral assumptions of IRT. First, there is an assumption regarding the *dimensionality* of the underlying ability or trait. While there are multi-dimensional IRT models (MIRT), the traditional IRT model requires that a single trait or ability accounts for an individual's θ score. When this assumption of the data holds, the examinees can be placed along a single, meaningful scale (Hambleton et al., 1991). Second, there is the assumption of *local item independence*. When the items on an assessment are locally independent, a response to any item is independent of a response to any other item on the same assessment for a given individual. This assumption allows us to determine the probability of an individual response pattern occurring given the individual's ability or trait level (Hambleton et al., 1991; Lord, 1980). If either of these assumptions is not met, item and person parameters will not be properly estimated and thus, indefensible.

In addition to these assumptions, an assessment of model-data fit is also important in IRT. A poorly specified model creates problems with estimating both item parameters and θ scores. Consider the following: An analyst mistakenly specifies a model which only specifies two parameters when in fact the data fit a model consisting of three item parameters. Because the pseudo-guessing parameter has not been specified, the θ values may be over-estimated as the individual's ability to correctly guess the answer has not been taken into consideration. Guessing is not considered to be included in ability and, as such, it should not be allowed to unduly influence scores. While IRT provides distinct advantages to classical methods of analyzing assessment data, these advantages come with several very restrictive assumptions which, if violated, calls into question the validity of the results.

In order to assess whether it was appropriate to employ an IRT model with this data, we decided to first empirically determine the dimensionality of the items by conducting an exploratory factor analysis (EFA) with an oblimax rotation on a randomly selected half of participants stratified by country (N = 3,965). [35] Should a one-factor model provide a good fit to the data, we would be able to proceed with IRT analyses. Should a multi-factor model provide a good fit to the data, the dimensionality assumption required by IRT methodologies would be violated. In that case, we proceed by examining the results of the EFA and confirming the factor structure using the second half of the sample (N = 3,964). All analyses were conducted in MPlus (Muthén & Muthén, 1998–2012; Version 6.12) and adjusted for any clustering of the data due to sampling design.[36] Responses were treated as ordered categorical data to account for the skewed nature of the data.

[35] An oblimax rotation was chosen to account for the hypothesized correlation between factors.
[36] In Tajikistan—but not in Uzbekistan or Kyrgyzstan—up to two individuals per household were administered the non-cognitive skills module. To account for any non-independence of the data that may occur due to individuals being nested in households, we used the Type=Complex and Cluster=psuid commands in MPlus.

Once we determined a factor structure that provided a good fit to the data, we created individual scores on each of these factors using refined factor scoring techniques. As detailed above, factor scoring is preferable in this case to traditional sum scoring methods given that factor scores account for: (1) the weight of individual item loadings; and (2) shared variance between the items and the factors *and* measurement error (DiStephano, Zhu, & Midrila, 2009). Factor scores were created using maximum a posteriori (MAP) estimation in MPLUS, which accounts for the non-normal distribution of item response (Muthén & Muthén, 1998–2012).

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).[37] 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 < 95% CI < .034).[38] 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).[39] 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).[40] This model was uninterpretable due to factor loadings above 1.

Table B1. 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

[37] 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).

[38] 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).

[39] 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.

[40] 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.

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	0.900	0.013
Reading Comprehension			
13.	Reading Comprehension Item 13	0.800	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	0.010
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	0.010
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

Interpretation and Future Directions

Our analyses indicated that the data from the cognitive skills module is best represented by three related factors that correspond to some—but not all—of the five cognitive skills described above. For example, our analyses indicated items 1-12 all indexed the hypothesized underlying executive functioning skill of Working Memory, while items 13-17 corresponded to the hypothesized underlying domain-specific skill of Reading Comprehension. Substantively, this indicates that individuals that have higher Working Memory factor scores are better able to temporarily store and manipulate information that is necessary for domain-specific cognitive tasks such as reading comprehension (Baddeley, 1992). Individuals with higher Reading Comprehension scores have a better ability to read and process text and understand its meaning than individuals with lower Reading Comprehension scores (National Reading Panel, 2000).

The other factor represented in the data is a combination of items meant to index facets of both Literacy (items 18-21) and Numeracy (items 22-27). This pattern of relationships can be understood in that the Information Comprehension items all involved number recognition (a component of numeracy), while the Numeracy items all tapped the ability to locate and use information contained in various formats such as advertisements and graphs (a component of information comprehension). Individuals who score highly on

Informational Numeracy have the ability to recognize and manipulate numbers contained in and represented by various formats.

There are three things to consider when interpreting the above analysis. First, the factor scores created through the factor analysis procedures described above are not invariant across different tests assessing cognitive ability. While such scores could have resulted from using IRT methodologies, we have evidence that using IRT with this cognitive assessment is not defensible given the likely violation of the assumption of dimensionality and as a result, item dependence. As such, we proceeded with creating refined factor scores that—although they do not inherently have the property of invariance—reduce the amount of measurement error contained in the scores. It should be noted, however, that invariance is a property that can be assessed through the use of factor analytic methods. Second, many of the items included in the cognitive skills assessment are not "clean" items. That is, they assess more than one skill at the same time: Items meant to tap the construct of Arithmetic, for example, also involve elements of reading comprehension and information comprehension. The factors—particularly Reading Comprehension and Information Numeracy—are thus highly correlated, which may be problematic for establishing predictive validity. To address this, we recommend that future analyses with this data consider a bi-factor analysis in which orthogonal or non-correlated grouping factors are created by allowing a "general" trait to correlate with the items (Reise, Moore, & Haviland, 2010). Finally, as noted in footnote 2, we were limited in our ability to discriminate between correct, incorrect, and missing answers due to issues in data processing. Given that missing answers were all recoded to be incorrect, it is likely that the scores underestimate the cognitive ability level present in the sample population. To address this, we recommend that future data collection activities carefully assess the type and extent of missing data to allow for better sensitivity tests of results to such specifications.

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Appendix C: Constructing Non-Cognitive Skills Scores Methods for Scale Development and Scoring

Prepared by Carly Tubbs, Ph.D. Candidate, New York University

Background and Measures

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 C1, below; Duckworth & Guerra, 2012). These non-cognitive skills can be conceptualized as falling into two domains:

(1) *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). The survey assessed each of these five factors with three items in the short Big Five Inventory (BFI-S) originally developed by John and Srivastava (1999) and later validated in large-scale panel surveys (Lang et al., 2011). Given its association with important labor market outcomes, assessed grit—a component of conscientiousness—was also assessed, with three items from the Grit Scale (Duckworth et al., 2007).

(2) *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). Although different cultures may differentially name, conceptualize, and prioritize such skills, socio-emotional skills and learning are of critical importance across all regions of the world (Torrente, Alimchandani, & Aber, in press). There does not currently exist an organization of socio-emotional skills similar to that developed for personality traits; as such this survey measures socio-emotional skills that are both valued by employers in countries in Europe and Central Asia (World Bank, 2009, 2013) and amenable to intervention efforts (Yeager & Dweck, 2012). These skills include: hostile bias (2 items; Dodge, 2003), decision-making (4 items; Mann, Burnett, Radford, & Ford, 1997), achievement-striving, and self-control (3 items and 2 items, respectively; Goldberg et al., 2006). In addition, the fixed vs. growth mindset, or the belief that intelligence is fixed versus malleable, was measured (4 items; Yeager & Dweck, 2012).

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 C1. Original 33 Items Included in the Non-Cognitive Skills Module[41]

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 enjoy working on things that take a very long time to complete?
Socioemotional 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?

[41] 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.

	Self Control
	Do you spend more than you can afford?
	Do you do crazy things and act wildly?
	Fixed Versus Growth Mindset
	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

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.

Given that the non-cognitive skills module has never before been administered in the countries of interest in this study, we decided to proceed by first conducting exploratory factor analyses (EFAs) with an oblimax rotation on a randomly selected half of participants stratified by country (N = 3,885).[42] In doing so, we are not making *a priori* assumptions about the factor structure of the module in these new contexts. Then, to support the EFA results, the factor structure was confirmed (in a confirmatory factor analysis, or CFA) using the second half of the sample (N = 3,887). All analyses were conducted in MPlus (Muthén & Muthén, 1998–2012; Version 6.12) and adjusted for any clustering of the data due to sampling design.[43] Responses were treated as ordered categorical data to account for the skewed nature of the data, and full information maximum likelihood (FIML) estimation was employed to handle missing data.[44]

[42] An oblimax rotation was chosen to account for the hypothesized correlation between factors.
[43] In Tajikistan—but not in Uzbekistan or Kyrgyzstan—up to two individuals per household were administered the non-cognitive skills module. To account for any non-independence of the data that may occur due to individuals being nested in households, we used the Type=Complex and Cluster=psuid commands in MPlus.
[44] FIML utilizes all available data points, even for cases with missing item responses, by assessing during parameter estimation missing data patterns as well as by using information from all available data points. While FIML does not impute missing data, its use of information from all observed data is conceptually similar to missing data imputation, where a missing value is computed conditioned on several other included variables (Muthén, Kaplan, and Hollis, 1987). In this sample, 120 cases did not have data on any of the items and were removed from the analysis.

Box C1: What is Factor Analysis and Why Do We Use it?

Factor analysis is a statistical technique that can be used to examine the relationship between observed items or *indicators* (see Table C1, above) and unobserved latent constructs or *factors* that are hypothesized to underlie the associations between indicators (in this study, openness, conscientiousness, etc.). There are three primary goals of or reasons to use factor analysis: (1) data reduction; (2) scale structure; and (3) to reduce measurement error. First, survey instruments provide a lot of data—some surveys to assess adult personality factors include over 500 items. Not only is it not practical to analyze that much data, but testing effects on multiple discrete indicators increases the likelihood of having a "false positive," or Type I error. Factor analysis assists with data reduction by establishing a lesser number of factors that account for the variation between indicators. Second, surveys are frequently designed to capture multiple constructs (in our study, various personality traits and socio-emotional skills) using items that may relate more strongly to some constructs than others. For example, in our study, the item "Do you think about how the things you do will affect your future?" may be a better indicator of Decision Making than, "Do you ask for help when you don't understand something?" Factor analysis allows us to understand the *internal scale structure* by quantifying the number of factors in the data and the extent to which items are related to each factor. Finally, 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, personality traits or socio-emotional 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 biases in regression analyses. Factor analysis allows us to adjust for *measurement error* by fitting an underlying model accounting for both variation among observed items and random error variance.

There are two primary types of factor analysis: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). While both EFA and CFA attempt to model the relationship between observed items using a smaller set of latent constructs, they differ in the *a priori* restrictions that are placed on the model. EFA is a data-driven technique that is primarily used when the factor structure (e.g, the appropriate number of underlying factors and the relationships of the items to the factors) is unknown, whether because the survey has never been administered before or is being administered in new contexts. In CFA, a researcher uses a strong theoretical foundation to specify at the outset the number of hypothesized factors and the patterns of how the items relate to the factors. This solution is then evaluated with respect to how well it fits the observed data. EFA is used most frequently early in the process of scale development, while CFA is used once the researcher has established the factor structure based on prior empirical and theoretical grounds.

Once we determined a factor structure that provided a good fit to the data, we created individual scores on each of these factors using refined factor scoring techniques. As detailed above, factor scoring is preferable in this case to traditional sum scoring methods given that factor scores account for: (1) the weight of individual item loadings; and (2) shared variance between the items and the factors *and* measurement error (DiStephano, Zhu, & Midrila, 2009). Factor scores were created based on the exploratory factor analysis solution using maximum a posteriori (MAP) estimation in MPLUS, which accounts for the non-normal distribution of item response (Muthén & Muthén, 1998–2012).

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).[45] 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.[46] 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 C2, 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).[47]

Table C2. 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?	0.360	0.020
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

[45] 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).

[46] 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).

[47] 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.

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 properties.	0.697	0.008
22.	You have a certain personality and not much can be done to change that.	0.704	0.008

Interpretation and Future Directions

Our analyses indicated that the data from the non-cognitive skills module is best represented by five factors that correspond to some—but not all—of the 11 personality traits and socio-emotional skills described in Table C1. For example, our analyses indicated that items 19-22 and 16-18 index the hypothesized underlying socio-emotional skills Fixed Versus Growth Mindset and Achievement Striving, respectively. Substantively, this indicates that individuals that have higher Achievement Striving factor scores tend to strive to go "above and beyond" and to do more than is expected of them, while individuals who have higher Fixed Versus Growth Scores tend to believe new skills can be learned.

The other three factors represented in the data are combinations of items meant to index both personality traits and socio-emotional skills; this pattern of relationships can be understood in that certain personality traits tend to be related to certain learned attitudes and skills. For example, our factor of Decision Making consists of items originally thought to index both decision-making skills and the trait of grit. In this case, individuals who think carefully and thoroughly about the repercussions of their decisions and behaviors (see items 12–15) tend to follow through with their actions (see item 11)—perhaps anticipating the repercussions of not following through. Our factor of Workplace Attitudes and Behaviors consists of items meant to index both Grit and Hostile Bias. Individuals who work very hard when others take a break (see items 6–8) may tend to feel that others take advantage of them or are mean (see items 9–10). Thus individuals who score higher on this construct may be workers who work hard and are innovative but perceive interactions with others as hostile; individuals who score lower on this construct tend to work less hard and on discrete projects, without perceiving workplace interactions as negative. Finally, our construct of Openness to New Ideas and People reflects items thought to index the personality traits of extraversion, agreeableness, and openness. Individuals who score high on this construct are social and open to new ideas, people, and things (see items 1–5).

There are two plausible reasons why the data did not reflect the expected 11 traits and skills. First, only 2–4 items were used to originally index each trait/skill; this may not have been enough to validly and reliably fully "capture" the constructs of interest. Instead, these items appear to reflect weak to moderately related aspects of a trait/skill that co-vary with aspects of other traits/skills. This is unsurprising given demonstrated correlations between: (a) Big Five personality traits (Digman, 1997); and (b) personality traits and socio-emotional skills (McAdams, 1995). To address this issue, future surveys should consider including a broader range of items to represent each trait/skill. A second explanation that we cautiously proffer is that the items do not relate to each other in the same way in Tajikistan, Uzbekistan, and Kyrgyzstan as in the samples from which the items were developed. For example, in the Grit scale in this sample, "finishing what was begun" is not related to "enjoying working on things that take a long time to complete." In ECA contexts, grit might not be well indexed by such behaviors. To investigate this, future research should: (1) conduct qualitative research to better understand how these traits and skills are understood in ECA contexts; and (2) test for measurement invariance between the non-cognitive items administered in this study and in other studies.

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Appendix D: Summary Tables

Employment Rate

Table D1. Employment Rate by Age Cohort

Age Cohort	All (%)	Male (%)	Female (%)
16-19	27.7	34.6	22.3
20-24	63.1	69.8	56.7
25-29	74.4	90.3	62.1
30-34	78.6	91.7	65.7
35-39	81.3	93.4	72.0
40-44	83.9	94.3	76.2
45-49	80.6	92.5	69.5
50-54	77.2	90.5	65.6
55-59	61.8	80.5	45.0
60-64	46.7	64.5	34.4
Total	64.4	76.2	54.5

Excluding current migrants.

Table D2. Employment Rate by Consumption Quintile

Consumption quintile	All (%)	Male (%)	Female (%)
1	59.5	73.7	48.1
2	65.4	80.5	53.2
3	63.2	73.7	54.3
4	68.6	77.9	60.8
5	65.0	75.6	55.6
Total	64.4	76.2	54.5

Excluding current migrants. Working-age population (16-64).

Table D3. Employment Rate by Rural/Urban Location

	All (%)	Male (%)	Female (%)
Urban	62.5	73.2	54.0
Rural	65.6	78.0	54.9
Total	64.4	76.2	54.5

Excluding current migrants. Working-age population (16-64)

Table D4. Employment Rate by Education Level

Education level	All (%)	Male (%)	Female (%)
Less than secondary	58.5	78.2	39.0
Secondary general	73.5	89.8	57.8
Secondary technical/special	82.0	92.3	71.8
Tertiary	82.6	92.1	75.3
Total	77.3	90.5	65.2

Including current migrants. Population aged 25-64 y.o.

Labor Force Participation Rate

Table D5. Labor Force Participation Rate by Age Cohort

Age cohort	All (%)	Male (%)	Female (%)
16-19	29.5	37.3	23.3
20-24	66.0	71.3	61.0
25-29	76.3	92.5	63.7
30-34	80.7	93.8	67.9
35-39	83.5	95.3	74.4
40-44	84.1	94.3	76.5
45-49	81.4	93.4	70.3
50-54	79.6	92.7	68.1
55-59	62.7	81.9	45.5
60-64	46.7	64.5	34.4
	0.0	0.0	0.0
Total	65.2	76.7	55.5

Excluding current migrants.

Table D6. Labor Force Participation Rate by Consumption Quintile

Consumption quintile	All (%)	Male (%)	Female (%)
1	60.9	74.9	49.6
2	65.4	80.9	52.7
3	64.1	73.4	56.3
4	69.4	77.9	62.2
5	65.6	76.4	55.9
Total	65.2	76.7	55.5

Excluding current migrants. Working-age population (16-64).

Table D7. Labor Force Participation Rate by Rural/Urban Location

	All (%)	Male (%)	Female (%)
Urban	64.4	74.5	56.2
Rural	65.7	77.9	55.0
Total	65.2	76.7	55.5

Excluding current migrants. Working-age population (16-64)

Table D8. Labor Force Participation Rate by Education Level

Education level	All (%)	Male (%)	Female (%)
Less than secondary	60.2	79.9	40.7
Secondary general	74.3	90.5	58.8
Secondary technical/special	84.0	94.7	73.4
Tertiary	84.2	93.7	76.9
Total	78.6	91.8	66.5

Including current migrants. Population aged 25-64 y.o.

Employment Status

Table D9. Employment Status by Age Cohort: All

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	27.7	1.8	3.1	67.4
20-24	63.1	2.9	3.1	30.9
25-29	74.4	1.9	1.9	21.8
30-34	78.6	2.1	1.4	17.8
35-39	81.3	2.2	0.7	15.9
40-44	83.9	0.2	0.6	15.3
45-49	80.6	0.8	2.1	16.4
50-54	77.2	2.3	0.8	19.6
55-59	61.8	0.9	1.9	35.4
60-64	46.7	0.0	0.0	53.3
Total	64.4	1.6	1.7	32.2

Excluding current migrants.

Table D10. Employment Status by Age Cohort: Male

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	34.6	2.7	2.2	60.5
20-24	69.8	1.5	3.8	24.9
25-29	90.3	2.2	1.5	6.0
30-34	91.7	2.0	1.4	4.8
35-39	93.4	1.9	0.7	3.9
40-44	94.3	0.0	0.7	5.0
45-49	92.5	0.9	2.2	4.5
50-54	90.5	2.2	0.8	6.5
55-59	80.5	1.4	3.1	15.0
60-64	64.5	0.0	0.0	35.5
Total	76.2	1.6	1.8	20.4

Excluding current migrants.

Table D11. Employment Status by Age Cohort: Female

Age cohort	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
16-19	22.3	1.0	3.8	72.8
20-24	56.7	4.3	2.5	36.5
25-29	62.1	1.6	2.2	34.1
30-34	65.7	2.2	1.5	30.6
35-39	72.0	2.4	0.6	25.0
40-44	76.2	0.3	0.5	22.9
45-49	69.5	0.8	2.1	27.6
50-54	65.6	2.4	0.8	31.1
55-59	45.0	0.5	0.8	53.8
60-64	34.4	0.0	0.0	65.6
Total	54.5	1.7	1.6	42.1

Excluding current migrants.

Table D12. Employment Status by Consumption Quintile: All

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	62.8	2.4	4.0	30.8
2	68.3	1.0	1.0	29.8
3	65.9	1.9	2.1	30.1
4	70.4	1.4	1.1	27.1
5	67.6	1.9	1.0	29.6
Total	67.1	1.7	1.8	29.4

Excluding current migrants. Working-age population (16-64).

Table D13. Employment Status by Consumption Quintile: Male

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	77.2	2.8	3.4	16.5
2	83.7	1.4	1.1	13.7
3	76.7	0.8	2.4	20.1
4	79.9	0.9	0.9	18.4
5	78.2	2.4	1.6	17.8
Total	79.1	1.7	1.9	17.4

Excluding current migrants. Working-age population (16-64).

Table D14. Employment Status by Consumption Quintile: Female

Consumption quintile	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
1	51.1	2.1	4.4	42.4
2	55.5	0.6	0.8	43.1
3	56.8	2.7	1.8	38.7
4	62.4	1.8	1.4	34.4
5	58.0	1.4	0.4	40.1
Total	56.9	1.7	1.7	39.6

Excluding current migrants. Working-age population (16-64).

Table D15. Employment Status by Education Level: All

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	53.9	1.9	2.8	41.4
Secondary general	70.8	0.8	1.6	26.8
Secondary technical/special	80.5	2.2	0.6	16.7
Tertiary	81.4	1.7	1.1	15.7
Total	75.3	1.4	1.3	22.0

Including current migrants. Population aged 25-64 y.o.

Table D16. Employment Status by Education Level: Male

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	73.3	2.0	4.1	20.6
Secondary general	88.5	0.7	1.7	9.1
Secondary technical/special	91.3	2.6	0.6	5.5
Tertiary	91.1	1.8	1.0	6.1
Total	89.2	1.5	1.4	7.9

Including current migrants. Population aged 25-64 y.o.

Table D17. Employment Status by Education Level: Female

Education level	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Less than secondary	37.5	1.8	1.7	59.0
Secondary general	55.5	1.0	1.4	42.0
Secondary technical/special	70.5	1.7	0.6	27.3
Tertiary	74.4	1.7	1.2	22.7
Total	63.6	1.4	1.2	33.8

Including current migrants. Population aged 25-64 y.o.

Table D18. Employment Status by Rural/Urban: All

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	64.8	2.8	1.8	30.6
Rural	68.5	1.0	1.8	28.7
Total	67.1	1.7	1.8	29.4

Excluding current migrants. Working-age population (16-64).

Table D19. Employment Status by Rural/Urban: Male

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	75.5	2.9	2.5	19.2
Rural	81.2	0.9	1.5	16.4
Total	79.1	1.7	1.9	17.4

Excluding current migrants. Working-age population (16-64).

Table D20. Employment Status by Rural/Urban: Female

	Employed (%)	Unemployed (%)	Out of labor force	
			Discouraged (%)	Inactive (%)
Urban	56.3	2.7	1.2	39.8
Rural	57.3	1.1	2.1	39.5
Total	56.9	1.7	1.7	39.6

Excluding current migrants. Working-age population (16-64).

Educational Attainment

Table D21. Educational Attainment by Age Cohort: All

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	4.4	44.0	12.3	39.3
30-34	4.2	45.6	17.1	33.1
35-39	3.9	47.0	19.3	29.8
40-44	2.3	48.6	22.6	26.5
45-49	4.8	47.3	29.9	17.9
50-54	1.6	42.7	31.2	24.5
55-59	5.0	43.3	28.6	23.0
60-64	8.3	47.0	22.5	22.2
Total	4.0	45.6	22.4	28.0

Excluding current migrants.

Table D22. Educational Attainment by Age Cohort: Male

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	2.9	51.1	10.5	35.5
30-34	5.1	44.1	18.0	32.8
35-39	3.4	51.3	20.9	24.4
40-44	2.9	52.5	19.2	25.4
45-49	6.0	43.4	30.8	19.7
50-54	0.9	41.5	38.5	19.2
55-59	5.5	39.5	33.0	22.1
60-64	8.5	47.1	22.9	21.5
Total	4.0	46.3	23.8	25.9

Excluding current migrants.

Table D23. Educational Attainment by Age Cohort: Female

Age cohort	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
25-29	5.5	38.5	13.8	42.2
30-34	3.3	47.0	16.3	33.5
35-39	4.3	43.7	18.1	33.9
40-44	2.0	45.6	25.1	27.3
45-49	3.7	51.0	28.9	16.3
50-54	2.3	43.7	24.8	29.1
55-59	4.5	46.8	24.7	23.9
60-64	8.1	46.9	22.3	22.7
Total	4.0	44.9	21.3	29.8

Excluding current migrants.

Table D24. Educational Attainment by Consumption Quintile: All

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	10.1	55.5	15.8	18.6
2	4.0	56.0	21.5	18.5
3	1.8	46.5	25.2	26.5
4	1.9	37.7	25.0	35.3
5	2.7	34.2	24.0	39.0
Total	4.0	45.6	22.4	28.0

Excluding current migrants. Population aged 25-64 y.o.

Table D25. Educational Attainment by Consumption Quintile: Male

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	10.3	56.7	18.4	14.6
2	3.9	57.9	22.7	15.5
3	2.8	48.7	24.7	23.7
4	2.0	36.4	25.4	36.2
5	1.7	34.8	26.9	36.6
Total	4.0	46.3	23.8	25.9

Excluding current migrants. Population aged 25-64 y.o.

Table D26. Educational Attainment by Consumption Quintile: Female

Consumption quintile	Less than secondary (%)	Secondary general (%)	Secondary technical/special (%)	Tertiary (%)
1	10.0	54.5	13.7	21.8
2	4.0	54.4	20.6	21.0
3	0.8	44.7	25.6	28.9
4	1.8	38.8	24.7	34.6
5	3.6	33.7	21.5	41.2
Total	4.0	44.9	21.3	29.8

Excluding current migrants. Population aged 25-64 y.o.

Table D27. Educational Attainment by Urban/Rural: All

	Less than secondary ()	Secondary general ()	Secondary technical/special ()	Tertiary ()
Urban	3.4	30.8	24.4	41.3
Rural	4.4	54.7	21.1	19.8
Total	4.0	45.6	22.4	28.0

Excluding current migrants. Population aged 25-64 y.o.

Table D28. Educational Attainment by Urban/Rural: Male

	Less than secondary ()	Secondary general ()	Secondary technical/special ()	Tertiary ()
Urban	3.3	31.0	25.8	39.9
Rural	4.5	55.5	22.5	17.5
Total	4.0	46.3	23.8	25.9

Excluding current migrants. Population aged 25-64 y.o.

Table D29. Educational Attainment by Urban/Rural: Female

	Less than secondary ()	Secondary general ()	Secondary technical/special ()	Tertiary ()
Urban	3.6	30.7	23.3	42.4
Rural	4.3	54.1	20.0	21.7
Total	4.0	44.9	21.3	29.8

Excluding current migrants. Population aged 25-64 y.o.

Appendix E: Cognitive and Non-Cognitive Skill Mean Scores

		Cognitive Skills			Non-Cognitive Skills				
		Memory	Literacy	Numeracy	Openness/sociability	Workplace attitude	Decision Making	Achievement Striving	Growth Mindset
	Total	-0.045	0.004	0.015	-0.023	-0.011	-0.016	-0.01	-0.035
Region	Urban	0.083	0.1	0.122	0.015	-0.033	-0.043	0.046	-0.026
Region	Rural	-0.125	-0.055	-0.052	-0.046	0.002	0.001	-0.045	-0.04
Gender	Male	-0.025	0.048	0.047	-0.03	-0.028	0.052	0.031	-0.1
Gender	Female	-0.062	-0.031	-0.011	-0.017	0.001	-0.07	-0.042	0.017
Consumption quintile	Quintile 1	-0.273	-0.194	-0.298	-0.258	-0.214	-0.102	-0.273	-0.083
Consumption quintile	Quintile 2	-0.151	-0.179	-0.155	-0.042	-0.017	-0.04	0.039	0.137
Consumption quintile	Quintile 3	0.011	-0.032	0.065	0.029	-0.038	0.12	-0.031	-0.058
Consumption quintile	Quintile 4	0.087	0.148	0.238	0.042	0.134	-0.038	0.124	-0.202
Consumption quintile	Quintile 5	0.086	0.273	0.203	0.102	0.062	-0.021	0.07	0.03
Age cohort: 16-35 years old	Young	-0.037	0.017	0.007	-0.016	0.026	0.027	0.044	0.044
Age cohort: 50-65 years old	Old	-0.079	0.012	0.002	-0.007	-0.012	-0.068	-0.098	-0.095
Employment status	Employed	-0.037	-0.003	0.036	0.004	0.017	0.006	0.022	-0.05
Employment status	Out of work	-0.081	0.024	-0.043	-0.087	-0.093	-0.123	-0.117	0.041
Sector of employment	Agriculture	-0.194	-0.337	-0.317	-0.327	-0.215	-0.098	-0.165	0.023
Sector of employment	Industry	-0.021	-0.021	0.082	-0.138	-0.136	-0.143	-0.154	-0.242
Sector of employment	Services	0.009	0.088	0.134	0.129	0.133	0.052	0.127	-0.013
Type of employer	SoE/Gov't	0.054	0.078	0.166	0.077	0.046	0.137	0.102	-0.113
Type of employer	Private Sector	0.133	0.098	0.164	0.069	0.146	-0.029	0.107	-0.319
Type of employer	Self-employed + other	-0.169	-0.101	-0.108	-0.075	-0.055	-0.076	-0.07	0.103
Educational attainment level	Secondary general	-0.208	-0.194	-0.192	-0.167	-0.12	-0.075	-0.153	-0.019
Educational attainment level	Secondary technical/special	0.116	0.17	0.196	0.055	-0.009	-0.014	0.038	-0.015
Educational attainment level	Tertiary	0.111	0.218	0.231	0.164	0.171	0.084	0.198	-0.075

Appendix F: SABER ECD 2013—Summary of policy options to improve ECD in the Kyrgyz Republic

Policy Dimension	Policy Options and Recommendations
Establishing an Enabling Environment	• Modify maternity leave policy to provide flexibility to parents, and ensure adequate financial support during early stages of a child's development • Develop secondary legislation to enforce implementation of Law on Preschool Education of the Kyrgyz Republic • Revive the process of the National ECD Strategy development, including development of a costed implementation plan • Continue to strengthen inter-sectoral coordination amongst participating government agencies, and between State and non-state stakeholders • Develop methodology to effectively measure and track financial investments in ECD • Consider increasing financial commitment to ECD sector, with particular focus on improving access to quality preschool education
Implementing Widely	• Undertake stocktaking exercise to document and map existing interventions • Reach children 0 to 3 with multi-sectoral services and reach their parents with education messages • Focus on raising the rate of exclusive breastfeeding • Address challenges associated with use of micronutrient supplements, including approval from Parliament • Increase coverage of preschool education; clarify various modalities for service delivery • Eliminate inequity in access to preschool education by increasing service provision and targeting children from lower socioeconomic families and rural locations
Monitoring and Assuring Quality	• Enhance data collection system • Monitor child development indicators in four interrelated domains of child development • Evaluate qualifications of ECD workers on an ongoing basis • Strengthen mechanisms to ensure compliance with service delivery standards and to measure the related outcomes • Develop standards of children aged 0 to 3 years

http://wbgfiles.worldbank.org/documents/hdn/ed/saber/supporting_doc/CountryReports/ECD/SABER_ECD_Kyrgyz_Republic_CR_Final_2013R.pdf.